Coláiste na hOllscoile Corcaigh, Éire
University College Cork, Ireland

Quantifying the impact of energy technology innovation on cost reductions

Thesis presented by
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for the degree of
Doctor of Philosophy

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September 2019

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Declaration

This is to certify that the work I, Alessia Elia, am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism.

Alessia Elia

Acknowledgements

This research would not have been possible without the guidance and support of a myriad of people.

First, I would like to thank my supervisors Professor Brian Ó Gallachóir and Dr Fionn Rogan for their support along my PhD journey. Their valuable insights and supervision were extremely helpful to me to finalize my work.

Secondly, I would like to thank also everyone contributed to this work. Their collaboration enriched my knowledge and enlarge my point of view. Specifically, thanks to Mitra Kami Delivand from UCC, Michael Taylor from IRENA, Alessandro Chiodi from E4SMA, and Gregorio Iglesias from UCC.

I would also thanks all my colleagues and friends, past and present, at the Environmental Research Institute (ERI) with who I have worked during these years: Eamonn Mulholland, Fionn Rogan, Paul Deane, James Glynn, Fiac Gaffney, Tomás Mac Uidhir, Peter Deeney, Xiufeng Yue, Emma Hanley, Mitra Kami Delivand, Evan Boyle, Clare Watson, Conor Hickey, Connor McGookin, Laura Mehigan, Tarun Sharma, Maarten Brinkerink, Camella Bailey, Parveen Kumar and Gideon Fadiran, Giada Venturini, Shivika Mittal, and Shiddarth Joshi.

Special thanks also to Magdalena Czyrnek-Deletre for the special friendship that welcomed me in Cork, her support was vital. Thanks also to Markus Voelklein for the refreshing tea breaks and his support to overcome many challenges. A super thank to my friend Emma Hanley for her patient to revise my work, and to be there with her friendship and knowledge. Thanks also to Aoife Long and Lucia Hermida Gonzales, and more in general to all the women, colleagues and friends, without their psychological support and friendship this journey would have been much harder.

Thanks to all the new friendship that I did during this Irish experience, I am grateful, they really made me appreciate even more this country and reinforce my idea that the world is full of wonderful people and we should go out of our comfort zone to meet them.

None of this work would have been at all possible if it weren't for my funders, and so I thank the NTR foundation, the Science Foundation Ireland, IRENA and Climate-KIC Pioneers program who all provided me with the funding and resources to carry out this work.

In the end special thanks to my family to always be there for me every time I need.

Siamo tutti guerrieri nella battaglia della vita…e io ho deciso di condurla.

Executive Summary

The alarming global warming risk has pushed for global consensus on the decarbonisation of the energy systems to achieve a low carbon future. In this context, it is necessary to invest in the deployment of emergent renewable energy technologies to accelerate the decarbonisation path of the national energy systems. The recent achievements in technology innovation for two mature renewable energy technologies, onshore wind and solar photovoltaic are generally recognised by decision-makers. However, this is not enough and most of current energy systems remain dependent on fossil-fuel resources to satisfy growing energy demands. Cost reductions are required across many more renewable technologies but the dynamics of how to achieve these cost reductions are poorly understood.

Deeper insights into the impacts of energy technology innovation on cost reductions are essential in order to accelerate the development and deployment of emerging renewables energy technologies. This thesis both highlights and addresses the current knowledge gap in our understanding of technology innovation, in the quantification of the drivers of technology cost reduction and in the innovation needs to accelerate technology cost changes.

The core of the thesis consists in linking together distinct fields of knowledge in an interdisciplinary manner: on one side the theory of technology cost reduction drivers and the energy technology innovation system framework, and on the other side analytical models to quantify the drivers of cost reduction and identify the innovation needs required to accelerate cost reductions.

The thesis firstly develops an understanding of the role of energy technology innovation on technology cost reductions. It explores the impacts of innovation along the different stages of development of a technology and identifies the main drivers of technology cost reductions. In so doing, the thesis also reveals the methods used to quantify multiple drivers of cost reduction and their analytical findings.

The thesis then investigates a new method to quantify technology cost reduction drivers based on an advanced bottom-up cost model for onshore wind. The disaggregation in cost components and techno-economic variables developed in this method generates clearer results than current approaches in the literature can provide. This includes improving the

causality link between costs components reduction and drivers and providing insights into the impacts of variables related to technical aspects and to manufacturing processes.

The thesis highlights the current limitations of attempts to incorporate energy technology innovation impacts into energy system optimization models, the main tools used to inform policy-makers on future climate actions. It further proposes a novel approach to explore technology innovation within current energy system optimization models. This approach links an energy system model with a historical innovation analysis, focusing on the prospects of wave energy development in Ireland. The combination of these two methods generates insightful results regarding the innovation needs required to accelerate technology innovation for wave energy that could not be captured with a single-method approach.

The key contributions of this thesis are the enrichment of our understanding of technology innovation, new insights and alternative improved methodologies to quantify technology costs reduction changes allowing to move beyond one-factor analyses, and novel methods to investigate the innovation needs required to accelerate technology cost reduction for emerging energy technologies. Moreover, an example of potential impact on the research community, this thesis lead to discussion between energy modellers and innovation practitioners about the contribution of technology innovation in energy system models.

Units and Abbreviations

1FLCs	One –Factor learning curves
ASY-70	Non-synchronous electricity limits 70%
BUCMs	Advanced Bottom-up Cost Models
COP21	21st Meeting of the Conference of Parties
CEM	Clean Energy Ministerial
DB	Domestic Bio-energy
EN	Employees numbers
ESOMs	Energy System Optimization Models
ETIS	Energy Technology Innovation Systems
ETSAP	Energy Technology Systems Analysis Program
EU	European Union
ETRI	Energy Technology Reference Indicators
kWh	Kilowatt hour
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
LBD	Learning by-doing
LBR	Learning by-researching
LBU	Learning by-using
LCA	Life Cycle Assessment
LCOE	Levelized Cost of Electricity
ES	Economy of scale
JRC	EU Joint Research Centre
KS	Spillover of Learning

KS (ind)	Spillover of Learning between stakeholders
KS (geo)	Spillover of learning between locations
IM-S	Supply-Chain dynamics
DM	Demand Market Dynamics
MI	Mission Innovation
MFLCs	Multi-Factors learning curves
MRE	Marine Renewable Energy (Wave, Tidal)
$MtCO_2$	Mega tonnes of Carbon Dioxide
MW	Megawatt
NREL	National Renewable Energy Laboratory
OECD	Organisation for Economic Co-Operation and Development
RD&D	Research Demonstration & Development
R&D	Research and Development
RES	Renewable Energy Sources
PV	Photovoltaic
ton	tonnes
TIMES	The Integrated Market Allocation Energy Flow Optimisation Model System
TIS	Technology Innovation System
TWh	Terawatt Hour
yr	Years
$	Dollars
€	Euros

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Chapter 1 : Introduction

1.1 Background

1.1.1 Climate Change & The Paris Agreement

During the UN climate change conference (COP 21) in Paris in 2015, the landmark agreement achieved between the participants focussed on the necessity of limiting global warming to well below 2°C above pre-industrial levels. Furthermore, the special report from the Intergovernmental Panel on Climate Change on achieving this ambition (IPCC-SR15) revealed the short timeframe remaining before a dangerous level of warming is reached. The current international political consensus points to the urgency of moving towards a low carbon energy system. It has therefore become a key concern of policymakers to transition from the current energy system to one comprising emerging renewable and low carbon energy technologies. The use of these technologies is necessary to limit the energy sector's impact on climate change. It is acknowledged that energy-related CO_2 emissions continue to increase, and in 2017 reached 32.5 Gt, with 41% of emissions from the power sector, followed by 25% from transport and 19% from industry [1].

In the last two decades, the success of energy technology innovations achieved for wind and solar-PV allowed these technologies to compete with incumbent fossil fuel technologies in most global energy markets. During this period, their price has fallen rapidly; the price of solar-PV modules fell 75% between 2010 and 2017, while, after 2008, the price of onshore wind turbines started to reduce reaching average prices below 1000 $/kW in 2017 [2]. This period also saw an accelerated penetration for these two technologies, and in 2017 the combined electricity generated by these technologies reached 1,519 TWh [1]. Despite this progress, this value represents only 6% of the total electricity generated worldwide, and less than 2% of total energy demand (as electricity consumption accounts only for 19% of total final consumption of energy). Despite a continued increase of global electricity demand since 2000, and future sustainable scenarios confirming an increase of electrification of the future energy systems, the majority of the total final consumption and electricity generated is dominated by fossil-fuels [1]. Hence, much more is required from national and international policies in order to see a rapid increase in deployment of these and other renewable energy, not only wind and solar-PV, and achieve GHG emission reductions to align with the rapid pace and scale of decarbonisation agreed during the Paris agreement [3, 4].

1.1.2 The growing need and challenge of innovation

In order to achieve the international energy goals in a short time, public bodies at national and international level are called on to allocate their resources to a wide variety of renewable energy technologies and to implement a long-term commitment for the development of emerging technologies. To ensure best use of financial resources, it is necessary to understand how energy technology innovation attributes evolve such as the reduction of technology costs, the increase of technology performance and technology market adoption [5]. Recently, energy technology innovation has been a decisive factor driving energy policies, for example, the Paris Agreement [6]. From this UN conference, innovation initiatives have arisen with the intent of investing in technology innovation of renewable energy technologies involving both public and private partners, for example, the Mission Innovation initiative [7]. Mission Innovation is a coalition of 24 countries and the European Commission who have pledged to increase investments and funding to help what they call clean energy technologies to reach technical and economical readiness to enhance their deployment. The high profile of Mission Innovation demonstrates the importance that is placed on technology innovation; however, the uncertainty of innovation outcomes will not help the simple Mission Innovation goal of doubling clean-technology research, development and demonstration expenditure in five years.

Scholars in the last two decades have recognised that energy technology innovation is not an autonomous process that simply occurs with time, but it is the result of the experience accumulated in the energy system. This experience drives the technology to overcome the innovation barriers along the innovation stages of development [8, 9]. One of the main bottlenecks (barriers) to technology deployment is the uncertainty regarding economic feasibility for the emerging energy technologies playing a key role in the future energy system. The uncertainty about what drives energy technology cost reduction is a major concern for policymakers, who seek to meet energy demand requirements with the lowest costs for society and in the most sustainable way. Cost reductions will likely be achieved for emerging energy technologies with the advancement of development, but the time constraints and investment required oblige decision-makers to promote policies that focus on accelerating these cost reductions.

1.1.3 Energy system modelling

Robust analyses are required to inform policymakers on how to accelerate the cost reductions of emerging energy technology. The typical tools used to develop an evidence base for policy support are quantitative energy systems models. The aim of these models is to represent the real interaction between supply and demand in an energy system under different policy scenarios. Amongst the different energy system modelling tools, long-term energy system optimization models (ESOMs) are used to investigate energy system transformation under different scenarios in medium and long-term analyses[1]. Example of these models are TIMES [10], MARKAL[11], MESSAGE [12] and Balmorel [13].

The integration of technology innovation dynamics into ESOMs is essential to understand technology cost reductions over time. A key concern for energy system modellers is to identify and better represent the variables in the energy models that are the most affected by technology innovation and with which dynamics these variables change in the energy system. Finding solutions in this field would provide a more robust representation of future energy scenarios that could help to understand how to accelerate emerging technology innovation in the energy system.

1.1.3.1 *Integrating technology innovation into energy system optimization models*

Initially, modellers implement exogenous technology cost reductions in the model, imposing exogenous cost reductions over time, drawing on new projections as they become available in the literature. The most common method to provide an endogenous representation of technology cost reduction in ESOMs is through the introduction of a logarithmic form of one-factor learning curves (1FLC) in the modelling code. 1FLCs link technology cost and capacity deployment [14, 15]. Criticisms emerged in [16], due to significant uncertainties arising from two main challenges: i) the real shape of cost reduction along the technology stage of development is not well represented with a 1FLC. For example, it does not provide a real representation of technology costs during, before, or at the early commercialization stage of development. ii) 1FLCs ignores other types of mechanisms that can contribute to technology costs.

Therefore, even if 1FLCs showed earlier technology adoption and larger cost reduction in ESOMs (for example [17]), the low credibility of results with 1FLCs and the high

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[1] These models provide the least cost optimal solution of the energy system with a partial equilibrium computational approach of production and consumption in the energy system.

computational requirements for implementation in ESOMs forced researchers to mostly prefer the exogenous representation of technology cost reduction in ESOMs, due to the oversimplified 1FLC assumption that cost reduce only with deployment. This exogenous parameter can be the result of an expert elicitation survey, and most probably it takes into account additional drivers and dynamics behind cost reduction. Some more complex forms of learning curves, like those including the effect of R&D policy (2FLC), were also adopted in some ESOMs as POLES, MERGE and ERIS which showed lower energy system costs and CO2 abatement costs [18], but also in this case the implementation had some limitations related to data availability of R&D investments, risk of parameters co-linearity, and difficulty to separate private and public R&D investments [18].

1.1.4 Energy technology cost through innovation

The state of art representation of technology innovation in ESOMs remains uncertain, simplistic and requires a large computational effort. In order to improve ESOMs representation of technology innovation, an investigation into the role of technology innovation in the energy system is required to identify what drives technology cost reductions along the stages of development. This kind of research requires an investigation into new or advanced analytical approaches to quantify these dynamics.

1FLCs are considered a simplistic method that do not truly represent all the drivers that are affecting technology cost reduction in the energy technology innovation system [16, 19]. Scholars point out that neglecting other multiple factors that drive the cost reduction of energy technologies can lead to an underestimation or overestimation of the role of technology deployment on cost reductions [20-22]. To advance the understanding of the impact of energy technology innovation systems on cost reduction and mapping the multiple drivers, the main tools used by the researchers are applications of more advanced regression models in the form of multi-factor learning curves (MFLCs) [23, 24]. Other works focused on advanced bottom-up cost model based on engineering cost assessment [25, 26].

The use of these models attempts to reduce the uncertainty behind the topic and to push the border of knowledge a step further, but this research field is still in its infancy, and there are many uncertainties. Thus, diversification of analyses and modelling approaches are required to increase the understanding of multiple drivers in the energy technology innovation system.

1.1.5 Trade-offs of using simple and complex modelling techniques to investigate technology cost reduction drivers

As described in sections above there is a lot of uncertainty on the best method to use to investigate drivers of energy technology cost reduction. A big challenge to resolve is the right trade-off between the use of more complex methods (which often have more realistic driver representation) and the use of simpler methods (but which provide more general answers).

Applying a 1FLC allows the identification of expected trajectories of cost reduction with technology deployment with a general learning parameter; this simple correlation between two variables gives little to no insight in the underlying mechanisms driving cost reduction because the reasons behind technology cost reduction are multiple as is described in section 1.2.2. The advantage is that 1FLC (theoretical model explanation in Appendix C) is recognised as a simple concept which (1) can be applied by energy modelers to set an endogenous trajectory of cost reduction in ESOMs, (2) can easily show to policy makers a quantification of investments required to obtain technology development and (3) can be used by industry to analyse the speed at which the manufacturing costs of the products they sell may decline [27]. However, the concept cannot prove that the experience, named as learning by-deployment (or learning by-doing) in 1FLC, is the cause of observed cost changes [19].

On the other side, multiple driver methods (both MFLCs and BUCMs) can provide an explanation of the mechanisms driving cost reductions, and in certain cases with BUCMs can create a better link of causality between cost reduction and multiple drivers (these two methods will be explored with more detail in Chapter 3). An improved understanding of technology learning drivers is extremely important to design and diversify policy and support measures to adopt for emerging renewable energy technologies, to understand the impact in the industry of endogenous and exogenous to the company learning, and to better identify dynamics of technology innovation behind cost reduction for energy modellers. The disadvantage is that the use of a more complex method improves the insights and lesson learned but also increases the uncertainties. Multiple driver methods make use of empirical data and modeller’s assumptions, thus increasing the drivers increases the factors that can hamper the accuracy and applicability of these methods [27]. A higher amount of data and assumptions are required to build a multiple driver method, but these cannot always be available or can rely on tacit information, which makes it more difficult for the analysis to be reproduced. At the current state of art, due to the infancy of multiple drivers methods, the use of multiple drivers analysis, even if the greater extent of the insights provided, may in certain cases be too complex to inform policy makers or the industry, but for this reason research in this field is necessary to overcome these barriers of knowledge gap.

1.2 Research Focus & Methodology

Uncovering the black box of multiple drivers behind technology cost reduction is of interest to numerous research fields, such as the technology transition in political science, energy economics, energy policy, energy innovation, and energy system modelling research.

This thesis makes use of the literature on driver theory and energy technology innovation to understand technology innovation framework impact on cost reduction and to identify the typical drivers responsible for cost reduction along the innovation stage of development of energy technologies. Moreover, the drivers are quantified with the use of an advanced bottom-up cost model (BUCMs). The thesis also uses scenario analysis with Irish TIMES and a qualitative historical innovation approach, to investigate technology innovation for a future emerging renewable technology, wave energy, and to identify the innovation needs required to accelerate its cost reduction in the upcoming years. In this way, multiple drivers of cost reduction are analysed, thereby overcoming the barriers of each single method.

1.2.1 Energy technology innovation system framework

Since the 1990s, because of the urgency to accelerate the decarbonisation paths of the energy systems, scholars have focused in understanding the dynamics of technological change. In studies such as [28, 29], the dynamics of technology diffusions, transition and substitution in the history were analysed. From these studies it became clear that the way technologies were treated in models used to project economic and environmental futures was highly stylized, because it was missing the representation of the drivers and mechanisms behind the technology life cycle.

Studies such as [8, 30] showed the need to study the dynamics of technological change through an innovation system perspective. An innovation system approach emphasizes that the life cycle of a technology develops in tandem with its corresponding innovation system [30]. From these works a variety of Innovation System approaches have emerged in the literature, such as the Technology Innovation System (TIS) [31, 32] and the Energy Technology Innovation System (ETIS) [33-35]. These two approaches vary from where the research interest have been posed; if it is concerned with the historical stages of energy technology innovation and how they are affected by the system dimensions (ETIS) or if the focus is on how the system functions contribute to the success of technological innovation (TIS) [36]. The interest of this thesis is on the stages of energy technology innovation and how this can be represented in energy system modelling, so ETIS framework is the most relevant conceptual background.

An ETIS framework includes all the socio-economic and institutional dimensions of an energy system which are affecting the innovation along the stages of development of an energy technology [9]. It is the analysis with a systemic perspective of innovation of technologies, thus, the study of technology stages of development, including drivers and mechanisms occurring in the energy system in which the technology evolves. An integrative approach which includes both the supply side and demand side of an energy system, in terms of actors, institutions, network and technology [9, 35]. These studies focus on energy technology, but they bring a systemic perspective in the discussion focusing also on system components. The various system components characterise what is understood about successful innovation, as well as what may be missing in case of failure , seeking to understand how technology innovation works and which kind of transformation in the energy system are needed [35]. Recent works quantified some technology innovation attributes that vary along the stages of development to measure the framework of ETIS [36, 37] The study in [36] applied this attribute framework for wind energy in China, which showed variation in time of these attributes related to an energy technology, such as technology costs, technology capacity, deployment to show the main contribution in the energy technology innovation system.

Based on the ETIS framework, this thesis reviews the holistic point of view of energy technology cost discussing the main drivers to technology cost changes in an energy system along the innovation stages of development. In this way the involvement of the system components of an ETIS as different actors, their networks and policy in technology cost reduction is understood, and what drivers cost reduction is investigated.

1.2.2 Drivers of energy technology cost reduction

The emphasis of this research is on the variation of multiple drivers along the innovation stages of development, specifically the thesis feeds into the provision of multiple drivers influencing technology costs, by investigating their asset along the innovation stages of development. Through the thesis chapter, this research uses both a historical technology innovation analysis that qualitatively identified the multiple driver and system components impact to technology innovation, and quantitative methods, as technology cost reduction analysis through an advanced bottom-up cost model and energy system optimization modelling analysis.

A driver responsible for cost reduction is concepts that describe specific dynamics occurring within an energy technology innovation system. Their investigation started during the first half of the 20th century to evaluate the cost reduction occurring in an airplane manufacturer, under this context, learning by doing was describing the time saved due to the increase of the worker's experience [38]. During the 1960s, different fields started investigating learning by-doing, including learning for energy technologies [39]. Nowadays, learning by-doing is considered one element of a more extensive concept defined as learning by-deployment which includes also the effect of learning by-using, which is the experience gained by customers, and learning by-interacting, which is the experience gained from collaboration with other partners allowing spillover of knowledge outside of a single manufacturer [19].

Within the energy technology innovation system framework, learning by-deployment is recognised as one of the key elements characterising the whole energy technology innovation system [9]. But in the system, other drivers responsible for cost reductions that are not necessarily linked with learning occurring within a company. For example, the role of learning by-researching is considered an important driver particularly at an early stage of development, such as the process of knowledge creation and the effort in research and development to improve energy technology performance [40, 41]. Once energy technologies deploy, the economies of scale at plant, device and manufacturing level are considered as contributing to cost reduction [42-44]. In the same way, knowledge spillover is not only achieved by the industrial partners, but also between different stakeholder categories such as researchers, entrepreneurs and decision-makers. Furthermore, knowledge spillover is achieved between regions, for example, between developed and developing countries [45-47]. Under these terms, the concept of learning by-interacting is widened to the whole energy technology innovation system. Another important aspect considered in this thesis is the role of market demand and the supply chain once technology readiness is achieved, and therefore also considers how the system responds to the introduction of the new technology in the market and how this influences cost reduction. Thus, the costs in the supply chain such as materials, external supplies, supplier labour and capital (supply-chain driver) [19, 48] and elements such as the amount of competitors manufactures, and the availability of a strict regulation to implement (demand market driver) [19, 49, 50] are considered important drivers.

1.2.3 Quantified method to investigate multiple drivers of energy technology cost reduction

Analysts in cost dynamics face the challenge of translating the contribution of these drivers to overall technology cost reduction in an analytical approach. It is clearly difficult to make accurate cost projections with a low level of uncertainty and poor linkage with causality the drivers' parameters with the cost reduction. The multiple drivers of cost reduction are characterised by a high grade of correlation to each other all along the innovation stages. Furthermore, the choice of parameters that can be used as proxy to measure the behaviour of drivers is arbitrary and subjected to a case-by-case basis and availability of data. MFLCs and advanced forms of bottom-up models (BUCMs) can be considered the main methods to investigate these drivers. This thesis reviews the findings from these two methods, and successively applies BUCMs exploring the cost reduction of onshore wind.

MFLCs are the main tool used in the literature and they are categorised as econometric regression models deriving from a cost minimization approach of a standard Cobb-Douglas cost function (See Appendix C for the learning curves theoretical model equation) [51]. Their intrinsic nature as a statistical regression model is criticised because the results obtained do not guarantee a causal relationship between drivers and cost reduction [20, 21]. Moreover, current state-of-art MFLCs mostly fail to represent high number of aggregated multiple drivers in the same model due to the uncertainty of variables and the difficulty to gather historical trend of data [24, 42, 52]. For these reasons the development of a BUCMs model is preferred in this work.

BUCMs are based on a bottom-up engineering assessment which allows cost disaggregation into its cost components [53, 54], these are then combined with a cost equation (defined by the modellers, see chapter 3 for the BUCM assumed in this thesis) which allows the impact of techno-economic variables on technology cost changes to be measured. The variables used in the cost equation are technical and economic parameters, and with a post-analysis each techno-economic variable is associated to a driver impact, according to specific driver categories defined in the analysis. The advantage of BUCMs is the capacity to link the trends of cost reduction with more quantifiable techno-economic variables, and therefore increasing the causality connection, for example, technology dimensions and quantity use of material variables. Moreover, it increases the specificity of the different cost components affected by these variables and the direct impact of each driver and better insights are provided for short-term cost analysis. For the first time in the literature, this thesis develops an empirical cost equation to understand and quantify four drivers of cost reduction for onshore wind.

1.2.4 Scenario analysis

To make a future projection of the impact of energy technology innovation in an energy system, a series of scenarios are developed with the Irish TIMES model. Irish TIMES is a model for the whole energy system of Ireland built on the TIMES modelling framework (The Integrated MARKAL-EFOM System) integrated with a dataset extracted from the Pan European TIMES (PET 36) project by the Energy Policy and Modelling Group (EPMG) at University College Cork (UCC), and calibrated with macroeconomic projections from the Economic and Social Research Institute (ESRI). It computes an inter-temporal partial equilibrium of the energy market with the objective to produce the least-cost optimal solution under different constraints. Thus, it provides a technology-rich basis for estimating energy system dynamics over a medium to long-term future [55-58].

In this thesis, a series of scenarios are analysed to investigate technology innovation for wave energy and the role of cost reduction to achieve deployment. The scenarios vary for renewable resources profiles, such as investment technology costs, resource availability, and electricity transmission profile, such as non-synchronous flexibility of the grid. This is done with the aim of including energy technology innovation analysis exogenously in the model with the use of a scenario sensitivity analysis approach, enabling variation of cost assumptions and other constraints. The scenario analysis is complemented with an innovation analysis of historical base on wind onshore that aims to investigate how technology innovation occurred in a winning technology example, showing what is needed in the energy system to achieve technology innovation and bring technology cost reduction down and the stakeholders involved. In this way, not only the different technology innovation scenarios are explored varying variables in ESOMs but what is needed to achieve that kind of technology innovation in the energy system can identified through the analysis of the innovation needs that helped a mature energy technology as wind onshore to move forward in its technology innovation during the previous decades.

Most importantly these findings are critically discussed in the prospective of to which extent they can be applied to the case of wave energy in Ireland.

1.3 Thesis Aim and Key Research Questions

This thesis acknowledges the importance of energy technology innovation to achieve a low-carbon energy system, and it aims to understand and quantify the role of technology innovation on technology cost reduction by identifying the drivers that lead to technology cost reductions.

The thesis addresses the existing research gap in relation to what drives technology cost reduction, and how energy technology innovation systems are involved in these dynamics. This thesis also contributes to providing answers on what is needed to accelerate technology cost reduction for emerging energy technologies.

A mix of methods is used to deliver on these aims. The methodology encompasses the energy technology innovation framework and drivers of learning concept, the application of bottom-up cost models and analysis with energy system optimization models. This will improve the knowledge base that underpins policy decisions on how to enhance energy technology innovation of emerging energy technology and to achieve cost reductions.

The following key-research questions were identified that shaped and guided the research of this thesis:

- RQ 1. How consistent is the energy technology innovation system framework with the drivers' theory of energy technology cost reduction?
- RQ 2. What is the present state-of-art methodologies in quantifying the multiple drivers of energy technology cost reduction?
- RQ 3. What insights are gained into the multiple drivers of energy technology cost reduction by applying a state-of-art methodology to a new data set of wind energy technology cost components?
- RQ 4. How can the integration of historical analysis improve energy system optimisation modelling of emerging energy technology innovation?
- RQ 5. What are the innovation needs for a particular emerging energy technology (wave energy)?

Each chapter and annex of the thesis address at least one of these research questions, the following section outlines the correspondence of each chapter with the research questions.

1.4 Outline of Thesis

The thesis is made up of 5 chapters and an Annex. Chapters 2, 3 and 4 are articles for which I am lead author that are under review for publication in scientific journals. The Annex is the report of a workshop organised with the modelling community ETSAP and innovation practitioners from IRENA. The structure and flow of this thesis can be summed up by Figure 1-1.

Chapter 2 provides a deep understanding of the effect of technology innovation on cost reduction, analysing the contribution of multiple drivers on cost reduction along the innovation stages of development of a technology. An extensive review on the role of system components along the energy technology innovation system on technology cost reduction is carried out. Moreover, it presents the findings from the current methods used to quantify multiple drivers of cost reduction for two renewable energy technologies onshore wind and solar photovoltaic. The focus of this chapter is on showing the consistencies that exist between energy technology innovation system framework (ETIS) and the dynamics contributing to cost reduction, highlighting how the learning processes vary along the technology stages of development and the main stakeholders involved. It shows the state-of-art methods used, and where there is need for further improvements. (RQs 1, 2)

Chapter 3 applies a BUCM to quantify the drivers of cost reduction for a mature renewable energy technology, onshore wind at global level. A rich techno-economic dataset is used to generate the cost model. The proposed model is an alternative to MFLCs applications and it aims to stress a better causal relationship between costs and driver parameters. In this way, a better understanding and certainty in the results of drivers is provided. This chapter concludes by highlighting the need to investigate multiple drivers to better understand cost reduction and how to accelerate them, and the need of a rich dataset to improve driver quantification in the analysis (RQ 3).

Chapter 4 analyses a specific new renewable energy technology, namely wave energy. The potential for wave energy to become competitive in the long-term future in Ireland's energy system is explored. The focus is on investigating the minimum level of energy technology cost reduction required, and also, on identification of innovation needs to accelerate the achievement of technology innovation for wave energy. The proposed approach links an ESOM – Irish TIMES – used to provide cost optimal low-carbon technology pathways and an historical technology innovation analysis. The chapter highlights the limitations of the current ESOMs to capture alone the role of energy technology innovation in future scenarios, missing an endogenous and robust representation of energy technology innovation in energy system modelling. Indeed, to explore technology innovation the current model is complemented with the historical innovation analysis which highlights which innovation needs are required and also how the current models can help to explore them with scenarios sensitivity analysis. Nevertheless, historical energy technology innovation analysis alone could not project future possible energy system scenarios and costs for emerging technology, thus it needs the complement of an ESOM. The paper concludes by providing discussion on the innovation needs identified in the chapter for accelerating wave energy technology innovation and to allow it to become competitive in an Irish context (RQs 4-5).

Annex I summarises the findings of a workshop session on innovation that took place as part of the IEA-ETSAP workshop of 9th of November 2018 in Stuttgart. This session was organised as a consequence of my research on technology innovation, which uncovers the research gap with regards to technology innovation understanding and representation of it in ESOMs. The discussion during the workshop discusses how to represent technology innovation in energy system modelling. The energy modelling community ETSAP and the innovation practitioner exchanged opinions about the current methods applied, mainly the exogenous technology cost reduction or the endogenous learning curves. The findings highlight the limits of and issues with implementing innovation in the current long-term energy system models. This chapter concludes with remarks on possible future areas where the research community should focus to implement technology innovation in energy system models (RQ. 4)

The final chapter, Chapter 5, presents the conclusions of this thesis, and recommendations for future work.

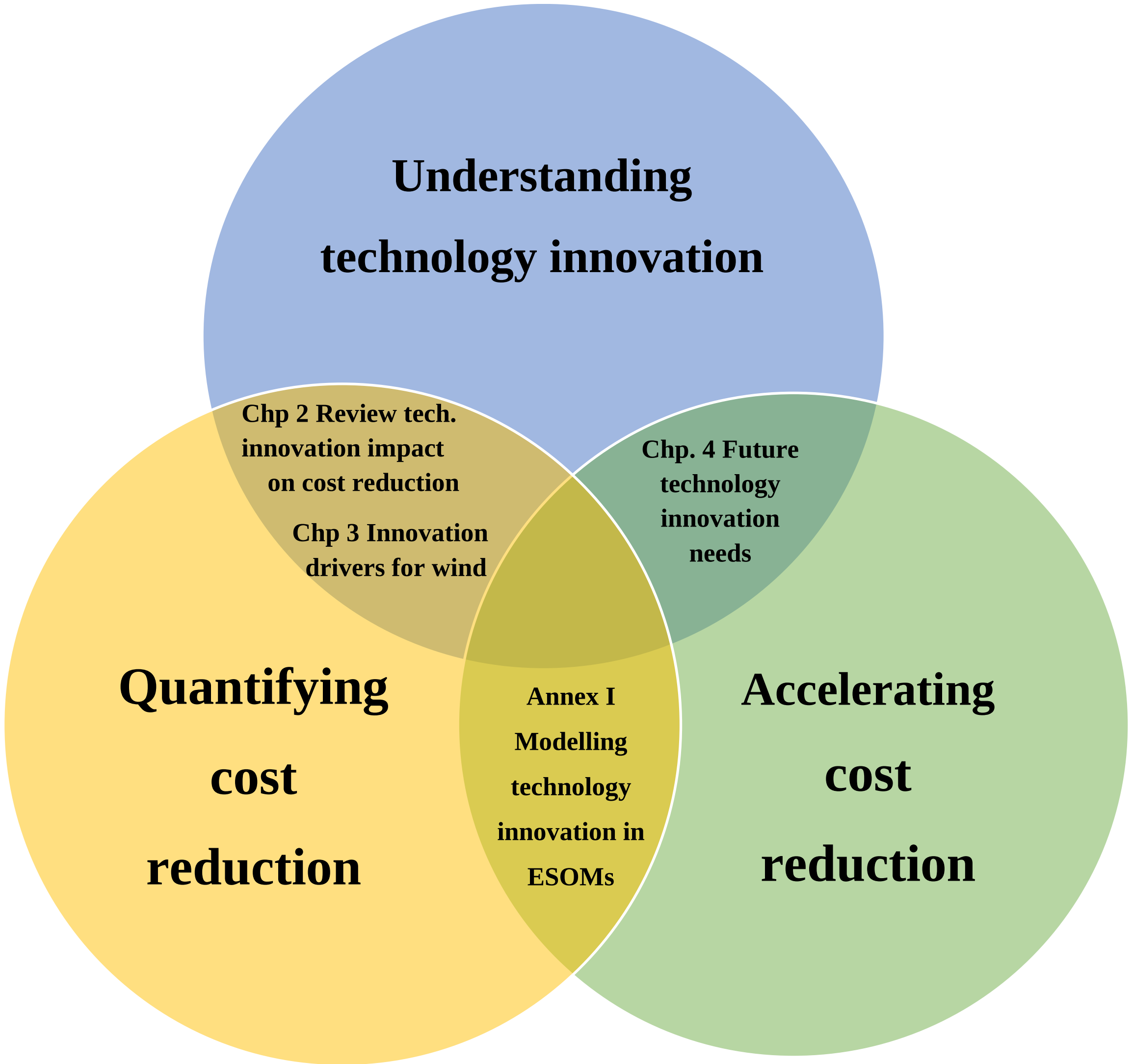


Figure 1-1. Scheme of the thesis

1.5 Outputs of the thesis

Peer-journal papers

- Alessia Elia, Alessandro Chiodi, Gregorio Iglesias, Brian Ó Gallachóir and Fionn Rogan. “Can wave energy be competitive?”, **Environmental Innovation and Societal Transition** (in Review)

- Alessia Elia, Mitra Kami Delivand, Fionn Rogan and Brian Ó Gallachóir. “Impact of Energy Technology Innovation on Renewable Energy Technology Cost Reduction”. **Renewable & Sustainable Energy Reviews** (In Review)

- Alessia Elia, Michael Taylor, Brian Ó Gallachóir and Fionn Rogan. “Wind energy cost reduction: a detailed bottom-up analysis of innovation drivers”. **Renewable Energy** (In Review)

Peer-reviewed Conference papers proceedings

- Alessia Elia, Alessandro Chiodi, Fionn Rogan, Seán Collins and Brian Ó Gallachóir “Ocean energy in Ireland: modelling and analysis of innovation needs for deployment by 2050”. **Proceedings of the 12th European Wave and Tidal Energy Conference**, 27th Aug -1st Sept 2017, Cork, Ireland

- Alessia Elia, Alessandro Chiodi, Fionn Rogan, and Brian Ó Gallachóir.” Ocean Energy for Ireland in 2050: Techno-Economic Feasibility and Innovation System Needs”. **Proceedings of the 37th Edition of International Energy Workshop**, 19th June-21st June 2018, Gothenburg, Sweden

Reports

- Alessia Elia, Fionn Rogan, Paul Durrant, Brian Ó Gallachóir. “Improving the understanding and modelling of innovation in the low carbon energy transition – workshop report”. **ETSAP report proceeding**, 2019.

Policy Brief

- Alessia Elia, Fionn Rogan and Brian Ó Gallachóir. “Wave Energy Innovation Needs”. Policy Brief for summarising findings related to research project ‘Our2050- Opportunity for Ireland in a Low-Carbon Economy’. Presented during final event 10th December 2018.

Presentations

- Alessia Elia, Fionn Rogan and Brian Ó Gallachóir. “Wave Energy Innovation Needs”. Our 2050 – Final-Project Event, Dec 10th 2018, Dublin, Ireland.

- Alessia Elia, Michael Taylor “Deeping the learning curve analysis for wind onshore technology”, ETSAP meeting, 9th November 2018, Stuttgart, Germany.

- Alessia Elia, Fionn Rogan and Brian Ó Gallachóir. “Ocean energy Innovation needs analysis”, 37th International Energy Workshop , 19th June-21st June 2018, Gothenburg, Sweden

- Alessia Elia, Fionn Rogan and Brian Ó Gallachóir “Ocean energy in Ireland: modelling and innovation needs analysis for deployment by 2050”, EWTEC conference 28th -31st August, 2017, Cork, Ireland

- Alessia Elia, Fionn Rogan and Brian Ó Gallachóir. “Delivering Ocean Energy Opportunities”. Our 2050 – Mid-Project Event, 22nd June 2017, Dublin, Ireland.

- Alessia Elia, Fionn Rogan and Brian Ó Gallachóir. “Modelling the innovation needs and value chains of Ireland’s energy transition”, MaREI Symposium, 5th-6th May 2016, Galway, Ireland.

Posters

- Alessia Elia, Fionn Rogan and Brian Ó Gallachóir. “Wave Energy Innovation Needs”. Scientific Advisory Committee Meeting, 11th February 2019, MaREI centre, Cork

- Alessia Elia, Fionn Rogan and Brian Ó Gallachóir. “Wave Energy Innovation Needs”. Our 2050 – Final-Project Event, Dec 10th 2018, Dublin, Ireland.

- Elia A., Fionn R., Ó Gallachoir B. Economics of Ocean & Marine Renewable Energy, Scientific Advisory Committee Meeting, 15th December 2016, MaREI centre, Cork

1.6 Role of Collaborations

This thesis is the result of my own work. However, I have collaborated with a range of researchers and experts in various disciplines for the formation of the various chapters. Collaboration was carried out with renewable energy and modelling experts from different institutions and universities. This chapter wants to clarify the role of these collaborations which have strengthened the output of my thesis. The chapters of this thesis will be three journal papers (in review) and a workshop report.

Chapter 2 is a paper under review in a peer-published journal paper for which I am the lead author. It was carried out in collaboration with Dr Mitra Kami Delivand, University College Cork which provided guidance and helped to design the review methodology. Professor Brian Ó Gallachóir and Dr Fionn Rogan provided guidance and reviewed drafts.

Chapter 3 is a paper under review in a peer-published journal paper for which I am the lead author. This work was carried out in collaboration with the Innovation and Technology Centre of the International Renewable Energy Agency (IRENA), specifically with Michael Taylor. I wrote this paper entirely and carried out all the analysis with regards to onshore wind cost reduction. IRENA provided me with the data, Michael Taylor provided guidance to design the research and discussed the results. Professor Brian Ó Gallachóir and Dr Fionn Rogan provided guidance and validated the model. Dr Fionn Rogan reviewed drafts.

Chapter 4 is paper under review in a peer-published journal paper for which I am the lead author. This work was carried out in collaboration with Dr Alessandro Chiodi, E4SMA srl. expert in energy system bottom-up models, and Dr Gregorio Iglesias, University College Cork an expert on renewable energy technology, specifically on wave energy. Dr Fionn Rogan and Dr Gregorio Iglesias provided guidance and discussed the results for further development of the paper. Dr Alessandro Chiodi provided guidance for the development of the Irish TIMES scenarios. Professor Brian Ó Gallachóir reviewed drafts.

Annex I is published as an ETSAP report of which I am lead author. This is the output of the Innovation section of the 74th ETSAP workshop organised in joint collaboration between ETSAP and IRENA that took place in Stuttgart in November. This was organised as a consequence of my research at UCC. This report was completed in

collaboration Paul Durrant, IRENA an expert on innovation which reviewed the draft. Dr Fionn Rogan and Professor Brian Ó Gallachóir provided guidance in editing the structure of the report and reviewed drafts.

Chapter 2

Impacts of Energy Technology Innovation on Renewable Energy Technology Cost Reductions

2.1 Abstract

Energy technology innovation framework plays a key role in achieving technology cost reductions, which at an aggregate level and using qualitative concepts, is increasingly well understood; however, the quantification of the multiple drivers of energy technology innovation remains poorly understood. This paper addresses this knowledge gap by presenting a systematic review of current practices. Despite the one-factor learning curves remain the most popular method for quantitative modelling of technology cost reduction the role of multiple drivers on cost reductions has been cited in previous studies. This review enriches our understanding of these multiple drivers by examining their impact along the different stages of technology development of a technology. The review shows the finding related to the variation in these drivers in the literature, and also shows that the development of multi-factor learning curve models and bottom-up cost models to quantify most of the drivers are still in their infancy. With a focus on onshore wind and solar-PV technologies, the review finds most of the published multi-factor learning curve analyses are focusing to address the impact of drivers related to i) manufacturing process improvements (i.e. learning by-doing) and ii) technology features improvements (i.e. learning by researching). This means that the other learning drivers such as spillover effects of knowledge across different technologies, stakeholders and geographical areas are still poorly quantified, despite their impact on cost reduction being recognised in the innovation literature. There is a danger that misinformed policies are currently being developed in the absence of a good understanding of these multiple drivers.

2.2 Introduction

There is increasing urgency to address the unsustainability of current energy systems to prevent an environmental tipping point. In the most recent United Nations Intergovernmental Panel on Climate Change (IPCC) report, a timeframe of twelve years has been set to cut fossil fuel usage by half, in order to limit the global increase of temperature to "well below 2°C above pre-industrial levels". This tight time constraint is pushing researchers to investigate how to accelerate innovation in emerging technologies to move more rapidly towards a decarbonised energy system. The use of energy system models to generate pathways to decarbonised energy system has become mainstream; however these models often rely on a simplified conceptualisation of how the processes of energy technology innovation lead to technology cost reduction [59].

Achieving economic feasibility is a mandatory requirement for a technology to achieve deployment and stable commercialization [36, 60-62] with cost reduction being one of the key variables of successful energy technology innovation [8, 63]. Policymakers are interested in policies that will encourage innovation of emerging energy technologies as well as policies that can improve the production and use of certain established energy technologies within an energy system. There is a growing interest in policies that can accelerate energy technology cost reduction. Evidence of this is Mission Innovation (MI), which emerged during the UN climate change conference (COP 21) in Paris in 2015. MI is a coalition of 24 countries and the European Commission who have pledged to increase investments in research, development and demonstration (RD&D) to help what they call clean energy technologies to reach technical and economical readiness [29] . However, RD&D investment is not the only policy required to help new technologies to reach economic feasibility and become competitive. Policies for overcoming deployment barriers to full commercialization of technologies in the market are also necessary [49, 64, 65]. This includes in the MI challenges a set of actions that increase collaboration between partners, facilitate knowledge spillovers and involve private sector investments [29].

Research on cost dynamics for energy technologies have concluded that learning, in terms of knowledge generated due to the accumulation of experience, is responsible for cost reductions [8]. Numerous studies [66-69] describe how costs reduce as new experience is gained by deployment using a one-factor learning curve (1FLC). Here a single parameter represents the experience obtained during the production process of a technology (learning by-doing), during the use or operation of a technology (learning by-using), and through the knowledge shared between the stakeholders involved (spillover of learning) [18, 66, 70, 71]. The simplicity of 1FLCs readily enables their use in energy systems optimization models to assess the technology cost reductions required to achieve deployment of renewable technologies, and thus an indication of the level of energy technology innovation required [18]. However, previous literature reviews [16, 18, 19, 72] have criticized 1FLCs for inadequately describing the complex dynamics leading to cost reductions, arguing that the contribution from other important drivers are missing. Furthermore, 1FLC is significant only for the technology innovation stages where commercialization is achieved and does not consider the cost reductions occurring during the initial stages of development [8, 61, 73-75].

The Multi-Factor Learning Curves method (MFLCs) [23, 24, 42], and, more recently, advanced versions of bottom-up costs models (BUCM) [25, 26, 76, 77] are emerging tools used to explain the influence of multiple drivers on cost reductions. Multi-factor learning curves are an advanced version of the 1FLC method and are based on the Cobb-Douglas production function with a cost minimization approach [51]. Bottom-up cost models derive from bottom-up cost engineering assessments of technologies [25, 26], which are used to disaggregate technology costs into their cost components; in addition, BUCMs link the cost components and drivers responsible for cost reductions quantitatively through the definition of a cost equation [25, 26, 77].

Previous studies acknowledge the influence of multiple drivers on costs [19, 70]. This review goes significantly further in enriching our understanding of these multiple drivers. It discusses their role within the context of the energy technology innovation system (ETIS), a framework which emphasizes the role of many non-technical elements responsible for advancing technology development within an energy system at different development stages [33, 35, 36, 60] (see Figure 2-4). In this way the current understanding of the role of energy technology innovation in renewable energy technology cost reduction through the cost drivers is explored. Moreover, this article reviews papers where the empirical evidence for multiple drivers in influencing cost reduction are described, highlighting the missing pieces in the literature to find solutions to quantify the drivers' impact. To do so the application of MFLCs and BUCMs on onshore wind and solar-PV are reviewed.

The chapter is organised as follows. Section 2 summarizes the methodology used to select the papers to review. Section 3 presents the impact of energy technology innovation on technology cost reduction along the innovation stages of development, from R&D to full commercialization, as it is described in studies exploring energy technology innovation. In this section the role of stakeholders and interaction of the innovation elements, and the drivers are presented. Section 4 discusses the limitation of 1FLCs in capturing the dynamics of cost reductions, using evidence for nuclear power plants as an example, and reviews the findings from MFLC and BUCM studies in quantifying the impact of the different learning drivers on cost reduction for onshore wind and solar-PV. It demonstrates the limitations of current analyses in representing the complexity of cost reduction in an energy innovation system. Section 5 provides conclusions and suggestions on potential future research in the field.

2.3 Methodology

The conceptual framework related to the impact of energy technology innovation on technology cost reduction along the stage of development of a technology is discussed by an extensive literature review. To do so, studies discussing energy technology innovation with a focus on dynamics driving technology cost reduction are reviewed. Therefore, papers studying energy technology innovation specific to energy technology diffusion pathways, technical performances, technology emissions impacts are excluded. The results from the review are discussed in an analytical framework which describes the course of cost reduction along the stages of development of a technology and the drivers and stakeholders' macro groups involved at each stage.

In addition, a systematic review is used to identify what drivers impact cost reduction along the stages of development and how much for two specific renewable energy technologies, onshore wind and solar photovoltaic for distributed applications. The following steps are taken to extract the relevant literature.

The electronic database 'Scopus' is used to collect the relevant studies published between 2000 and 2019. In the first step, the research terms chosen combines key terms related to technology costs reduction methods as "learning curve"," experience curve", "cost model", "knowledge spillover", "learning by-doing", "learning by-researching", and "return to scale" with terms related to energy technologies as "solar energy", "wind energy" "photovoltaic", "wind technology" and "solar technology". Within the same category the terms are combined with Boolean “PRE/”, while between the two categories with the Boolean “AND”. In this way all the papers using different approaches to evaluate cost drivers related to these renewable energy technologies are found. The total amount of results removing the duplicates is over 600.

In the second step, a case-by-case selection is performed by reviewing the title and the abstract to identify the papers discussing the methods used to quantify the multiple drivers responsible for cost reduction. All the papers related to other technologies, and not pertinent to the topic are excluded. After this second step, the total number of papers is 110.

In the third phase, a manual screening reading the remaining papers is done to exclude the applications of 1FLCs, qualitative methods and papers applying learning rates outputs from cost models as input into energy system optimization models to explore future deployment in an energy system.

As result, a total number of 32 peer-reviewed papers is obtained. From these, 23 analyse cost drivers for onshore wind and 16 papers focus on solar-PV. For onshore wind, only MFLCs approaches are found, while for solar-PV 2 papers apply BUCMs and 14 are applications of MFLCs. Figures below show the time series of publications over time about MFLCs and BUCMs (Figure 2-1,Figure 2-2), and the type of MFLCs and BUCMs analysed in the literature, reporting the number of publications for solar-PV and onshore wind and their geographical diversification (Figure 2-3, Table 2-1).

Table 2-1. Geographical diversification of papers reviewed

MFLC METHOD			BUCM METHOD	
	ONSHORE WIND	SOLAR-PV	ONSHORE WIND	SOLAR-PV
GLOBAL	7	9	-	2
EUROPE	6	-	-	-
CHINA	4	1	-	-
US	3	1	-	-
OTHERS	3	3	-	-

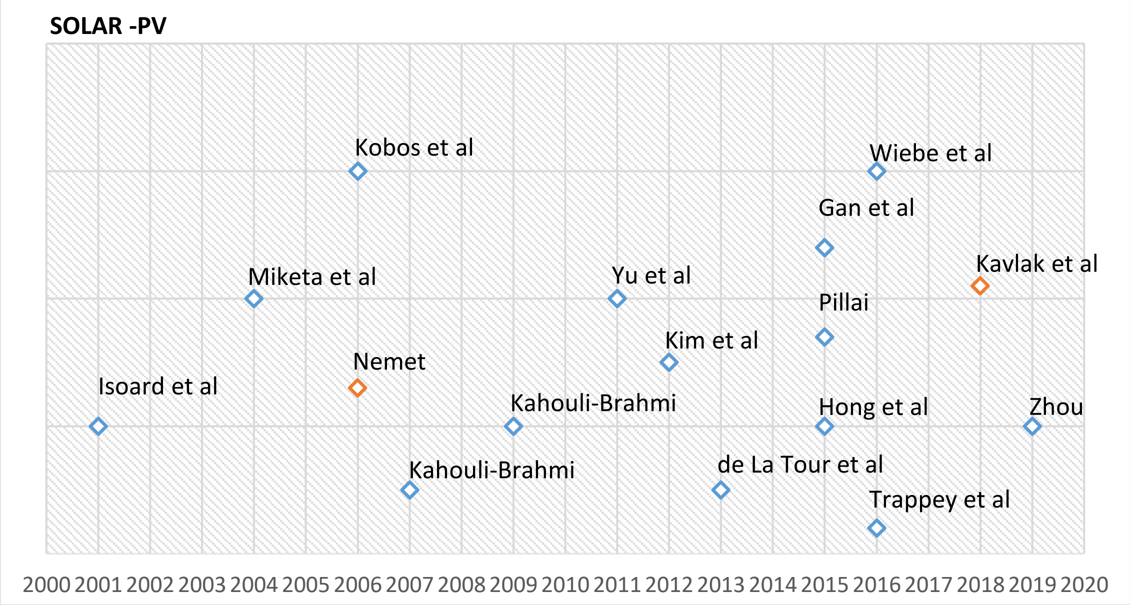


Figure 2-1. Solar-PV - time series of publications about MFLCs and BUCMs (y-axis high is only for showing details in the infographic, orange dots are for BUCMs publications)

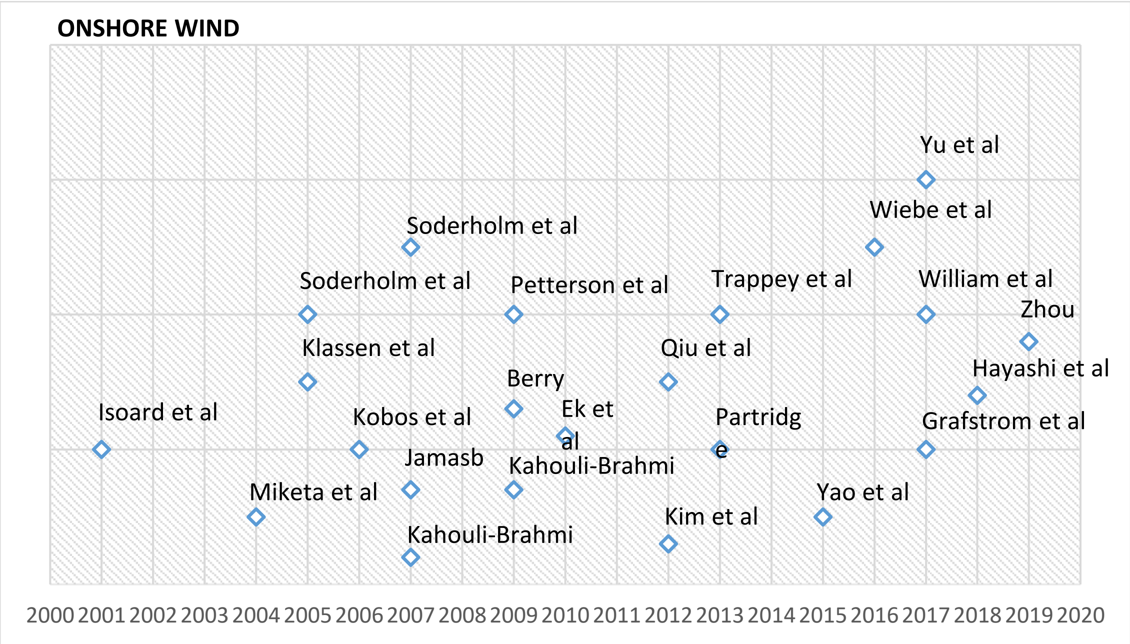


Figure 2-2. Onshore wind - time series of publications about MFLCs (y-axis high is only for showing details in the infographic)

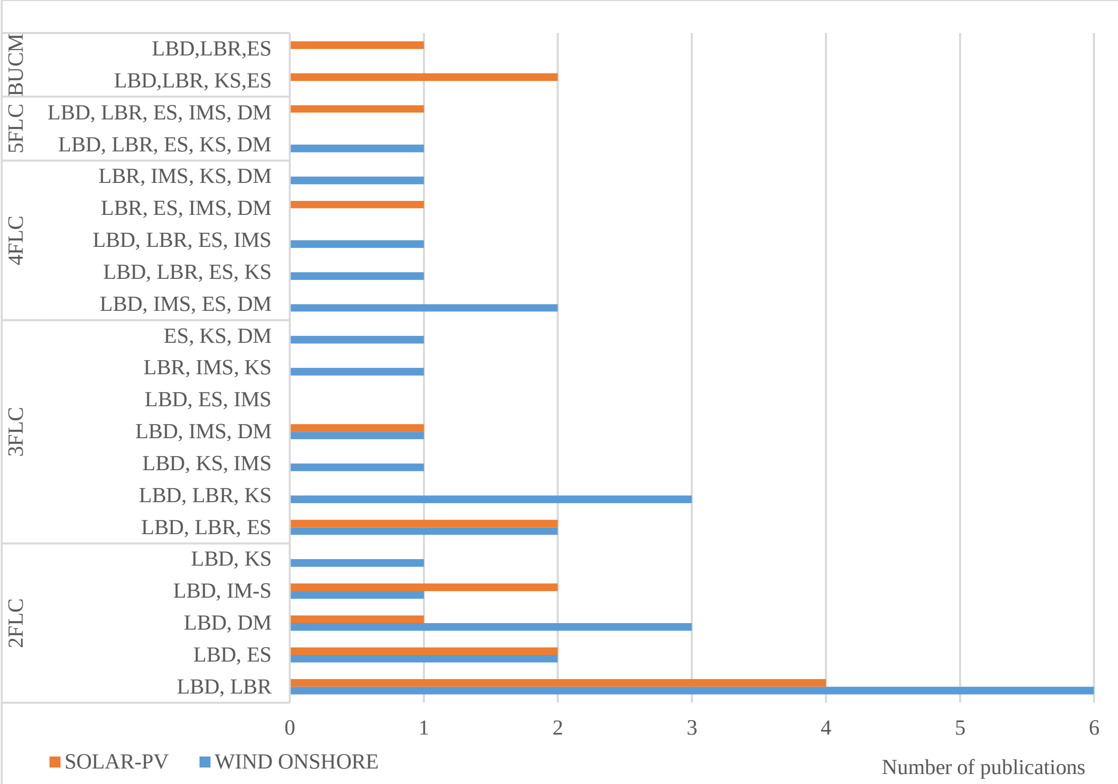


Figure 2-3. Number of publications analysing different types of MFLCs and BUCMs in the literature

2.4 Energy technology innovation characteristics and drivers of cost reduction

The drivers contributing to cost reduction within the stages of development of a technology can usefully be categorised as follows [19, 70, 75]:

(1) Learning by-researching, or by-searching, (LBR) driver describes cost reductions achieved due to the technical improvement of a technology as a consequence of knowledge creation during the research activities in the system [78]. This type of learning is usually represented as knowledge stock which also includes the knowledge depreciation as mechanism of negative learning (to see Appendix C – forgetting by not doing). Knowledge depreciation is the knowledge lost if the research is not pursued sufficiently regularly particularly at early stage of development [79, 80]. An example of knowledge depreciation is the case of ocean energy technologies and the research gap that occurred between the 1970s and 2000s before renewed interest from academia and industry in these energy technologies [81, 82]

(2) Learning by-deployment which can be disaggregated into its sub-components: learning by-doing (LBD), learning by-using (LBU), and spillover of learning (KS), which is also described in the literature as learning by-interacting. LBD relates to cost reductions

achieved due to experience gained during the production process, such as improvements of management and labour knowledge acquired [61]. LBU relates to improvements, in the manufactures process or technology quality, due to feedback received by users during the operational activities [83]. KS is related to cost reductions achieved due to knowledge exchange through interaction with other actors along the technology value chain as through benchmarking between industries and research centres (KS(ind)). It also involves knowledge exchanged between two different locations, as joint-ventures collaborations in new markets (KS(geo)) [45, 46]. Knowledge spillover is also partly due to the knowledge coming from the achievements in other technologies, which can be considered as the inter-industry spillover part of KS(ind) [84, 85].

(3) Economies of scale (ES) at device, plant and industry level also contribute to technology cost reductions [42-44]. Up-scaling at device level is particularly significant for renewable technologies to explore the positive or negative impact on costs, as in the case of onshore wind [44, 86, 87].

(4) Markets also affect cost reductions, in this case production market drivers explain the dynamics related to the supply-chain (IM-S), incorporating input materials availability and their market price, the cost of supplies, the variation of capital cost and salary labour costs [48]. Demand-side market accounts for the dynamics related to the sales market (DM), encompassing the increase of number of competitors and the implementation of new environmental regulation [49, 50]. Energy and climate policy measures are induced mechanisms for technology innovation, which can lead to cost reductions, as policies can enhance market deployment. In [80, 88, 89] the importance of market-pull policy measures on cost reduction such as feed-in tariff incentives during commercialization phase is argued. The literature is inconclusive on the estimation of this parameter as a learning driver [70], thus a specific policy driver is not considered in this review but it is discussed within the DM driver. It should be noted that poorly developed or delayed policy adoption could slow down the pace of cost reduction, and consequently the path of energy technology innovation [90].

These drivers occur along the stages of development and contribute to the different elements characterising the grand patterns of technology innovation contribute to costs reduction through these drivers [91] (Figure 2-4). The different drivers may have more or less relevance along the individual stages of development and they involve different macro-group of stakeholders as shown in Figure 2-5 and as discussed below.

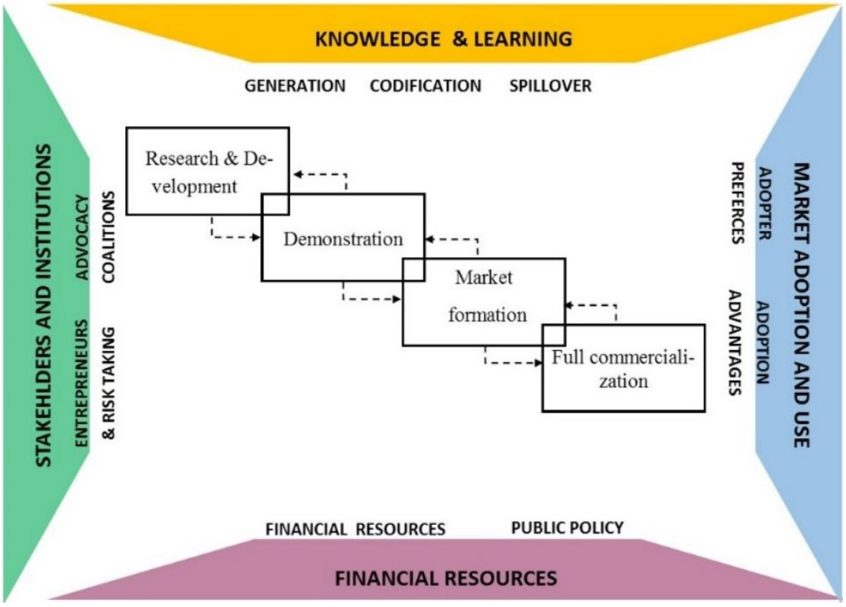


Figure 2-4. Energy Technology Innovation system framework (ETIS). It describes the stages of development (white squares) and the innovation elements involved in the innovation process (Frame). Adapted from [9]. Here, research and development stages are merged as one unique stage.

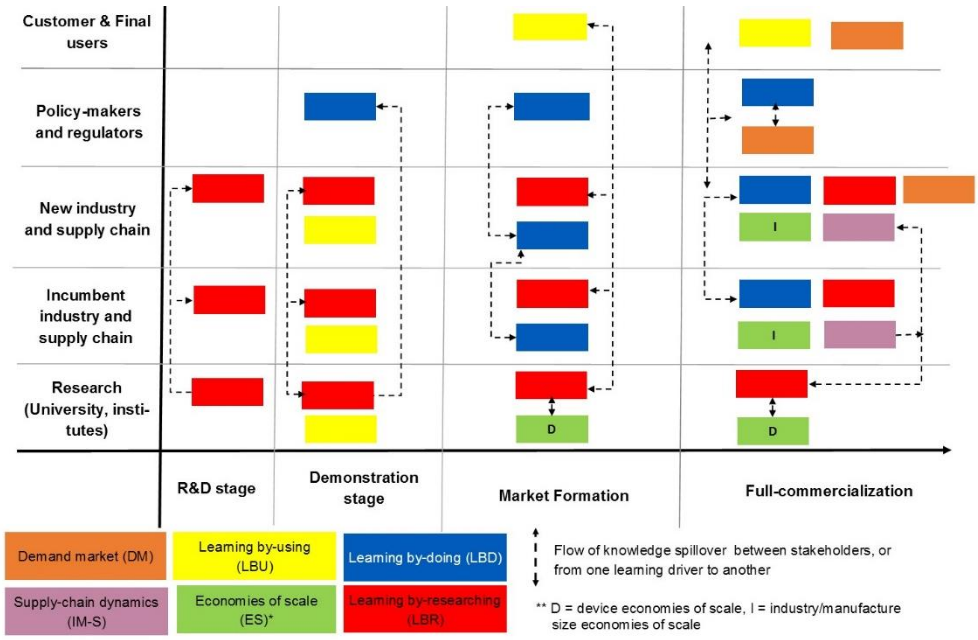


Figure 2-5. Learning drivers along the innovation stages and group of stakeholders involved. The stages of development are based on: [8, 9]. Macro-groups of stakeholders are used as described in the written part.

2.4.1 Research and development (R&D) stage

Starting at the R&D stage, the role of learning by-researching is primary and is enhanced by spillover which affects the pace of research activities and increases the effectiveness of R&D investments [92]. Knowledge can be shared between academic stakeholders and private partners through events, conferences, and joint research projects. Unpublished knowledge can be disseminated, and universities are knowledge providers for emergent technology developers to improve technology features and bridge the gap towards technology standardization [73, 83, 93]. Technology spin-offs can arise between different R&D programs leading to the emergence of new advanced technologies [84]. This was the case for example in light water nuclear power reactors which were first developed for military submarine propulsion [92]. Moreover, during this stage industry is mainly composed of a large number of technology developers, and the knowledge spillovers between them can offset the lack of resources and good practices in new products development [94]. Knowledge creation and spillover is frequently sustained mostly from governmental financial support with public investment [61, 95], (e.g. the Japanese solar PV-programme financed in the 1970s [8, 33]) and from funding institutions (e.g. the Carbon Trust in UK [96]). In certain cases, as for wind turbines and fuel cells, research was also financed from incumbent industries with an interest in expanding their business in new technology applications [97, 98].

2.4.2 Demonstration

During the demonstration stage, certain emerging technologies can experience challenges, demonstration plants may not reach the initial expectations and their commercial potential might be overestimated [64]. This can lead to a reduction of financial resources and consequently slow down or stop the process of learning that might be expected from testing devices at full-scale. For example, carbon capture and storage demonstration plants experienced declining financial support incurring in near-term stalling [99]. A continuous level of government support has positively influenced the achievement of innovation for renewable energy technologies as solar PV and biodiesel [100]. It can avoid the risk of a period without financial support (the valley of death) [101]. Moreover, private investors are necessary to complement public funding for demonstration plants [102, 103].

The demonstration stage provides a field for collaboration opportunities between new and incumbent industry with interest in the application of an emerging technology. The incumbent industry know-how can assist in reducing the barriers required to integrate a new sustainable energy technology in the current energy infrastructure, increasing the capability for market adaptation with lower construction costs, and lower negative environmental and social impact [103]. Feedback from full-scale testing can inform technology developers attempts to revise designs, as well as informing public government and research institutes about operational feasibility, standards and codes that can be implemented [104]. The exchange of knowledge and interaction between stakeholders is particularly necessary when there is insufficient of R&D funding to solve technical issues [19, 105, 106]. This kind of knowledge spillover is usually in contrast with private intellectual property and to happen it needs negotiation with private investors that wants to protect their business [102].

2.4.3 Market formation

The pattern of technology deployment in a market is described in the literature as a logistic function [44, 107]. In the initial, or formative phase, technology is deployed in protected markets, usually niche markets where market players are more sensitive to technical features, and performance advantages than to cost competitiveness [108]. Solar-PV was first used for space applications before the 1970s, and then in off-grid isolated niche markets during the 1980s. Onshore wind, by contrast, was deployed in commercial Californian market during the 1980s, where it could avail of advantageous market-push policies that guarantee safe investments in a competitive market [97]. In addition to public institutes, new knowledge creation also develops within industry, particularly in the new leading companies in the sector. Knowledge gained by manufactures about technology design features is usually protected by business, which makes it difficult to disaggregate learning by-researching in a firm from the effects of learning by-doing on cost reduction [61, 73]. Firms can take advantage of external knowledge and reduce the internal R&D effort. It has been observed that firms benefit more in locations characterized by a cluster of companies thanks to spillover [94, 109]. The role of formal networks developed to share knowledge, such as advocacy coalitions and strategic alliances is useful for all the actors to ensure markets for their products and supply chain formation, for example development of technical guidelines and training for service providers [98].

Industry is at its infancy during this stage and the number of small entrepreneurs increase when attracted by market opportunities. During this stage some industry players will be crowded out of the market due to the competition between different firms and technology designs [94]. Experience gained in manufacturing leads to improvements in production, operation and management, namely learning by-doing [61, 73, 78, 83, 110]. Niche market customers provide feedback on operation issues to researchers and entrepreneurial producers, namely through learning by-using, usually pushing to improve technology features, and to implement innovation in the production process which will reduce the business-risk for future diffusion [111]. Also policy-makers take advantage of feedback regarding public opposition to solve before a wide implementation of the new technology [112].

Moreover, a protected market allows testing of the first economies of scale at a device-level, by checking potential benefits in energy production, decrease of unit capital costs, and barriers occurring in regulation and construction of bigger devices [44, 61, 113]. In this way up-scaling of unit devices is usually achieved at the end of this stage [44]. To support initial market development, policy makers need to ensure that resources are mobilized in a consistent long-term policy framework. The strategies implemented should align both with the need of researchers, who expect feedback from the niche market to develop better routines, and the needs of private industry, which want confidence to invest [64, 95, 114]. The cooperation between these three stakeholder groups is also beneficial for the regulation learning process [115].

2.4.4 Full commercialization

Full-commercialization starts with a rapid market capacity expansion, and a strong industry growth towards a standardized structure [44, 107]. Learning by-doing in the whole industry, both technology producers and supply chain, is driving cost reductions during this stage. Knowledge creation is still happening, but learning by-researching is mainly achieved at industrial level with collaborations between companies and public research reduced [61, 73]. Learning by-using and knowledge spillover about deployment experience do still remain relevant drivers [19, 116]. For example feedback obtained from builders and installers thanks to implementation of the products in a market allows technical barriers to be overcome [117, 118]. Moreover, scaling-up at industrial level has production cost advantages due to industrial economies of scale [44]. Industrial learning by-researching, industrial economies of scale, can overlap the effects on cost reduction of learning by-deployment [19].

Market scale is observed during this stage, with technology success inspiring spillover from core markets to periphery markets [44, 113, 119, 120]. The capacity of a company to develop strategic alliances with partners in the new market allows for the adoption and use in markets with different rules and regulations [49, 83, 94, 121]. Moreover, the adoption of emerging technologies in new markets requires a certain lead-time, which depends on the readiness of the market to implement new regulatory processes and policy ability to facilitate new technology penetration [49, 121, 122]. Market dynamics, as for example, an increased amount of competitors in the demand market which reduces companies' margin for profit [20, 123], or changes in international trading rules [20, 124] and market structure regulation, such as anti-dumping duties, can modify prices of technologies [49, 125, 126]. Furthermore, renewable energy technologies are material and components intensive, and during full-commercialization their cost is sensitive to the quantity and quality materials and supply used and their unit price [23, 95]. Cost changes in the production market and supply-chain can also generate feedback loops with other learning drivers like to stimulate new economies of scale or learning by-researching to reduce the impact material price volatility and capital costs [16, 23].

2.5 Multiple drivers literature review

The previous section discusses how energy technology innovation system contributes to cost reductions through learning drivers. Here the authors explore the implications of 1FLC in failing to capture these drivers and explore the emerging literature that is addressing these limitations. As explained in [19], in addition to not correctly accounting for learning drivers, another failing of 1FLC is the assumption that a learning rate remains constant in time and along all the stages of development. These limitations can be clearly observed in the 1FLC for nuclear PWR shown in Figure 2-6.

Figure 2-6 describes the cost reductions in a period of time from mid-1950s to 1978 in US. Capital cost reductions are related to cumulative capacity installed, and during this period the technology moved from the demonstration to full-commercialization stage. Due to the size of the nuclear plants and the long lead-time required for construction, it is not possible to identify a specific market formation stage [127]. The results show a learning by-doing rate of 18% before 1970, and then the construction costs start to rise with capacity installed and negative learning is observed [18]

The negative correlation observed is associated with the difficulty to operate new and more reliable reactors under the new safety regulations implemented after the 'Three Mile Islands' nuclear disaster (lack of learning by-doing and learning by-using, and difficulty to adapt to new demand market dynamics due to regulation changes) [127, 128]. Moreover, the rush in scaling plant size with large-scale reactors (dis-economies of scale), and the lack of pervasive research activities to overcome the barriers of size scale and long lead-time also contributes to a cost increase (lack of learning by-researching) [128, 129].

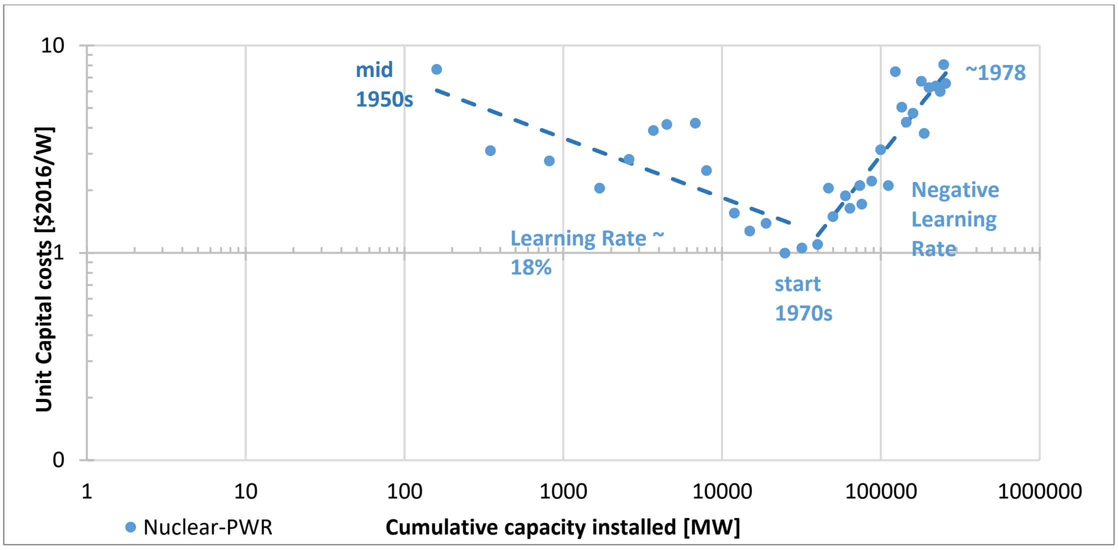


Figure 2-6. One-factors learning curves for nuclear PWR (log-log axis). Own elaboration from sources: (b) [128, 129].

In fact, several drivers are missing such as learning by-using, economy of scale, and market dynamics. For this reason, although Figure 2-6 shows a correlation between cost and cumulative capacity, the interpretation of the 1FLC can be misleading because the correlation is not the same as causality between the two variables [61, 73]. Moreover, Figure 2-6 shows that learning rates do not necessarily remain constant along the innovation stages of development of a technology. Thus, learning rates cannot be easily extrapolated to assess future experience-cost reduction.

To explore how these 1FLC limitations are being addressed in the literature, we focus on the main renewable energy technologies that are investigated with multiple driver methods in the literature, namely onshore wind and solar-PV, which both show a successful cost reduction path (Figure 2-7). The occurrence of development stages depends on location, thus about where the development occurs. For example, these stages could be different in the core and follower countries[2] [44, 130] where the market formation and full-commercialization may happen at different times. **Errore. L'origine riferimento non è stata trovata.** shows the incidence of various technology stages of onshore wind and solar-PV development.

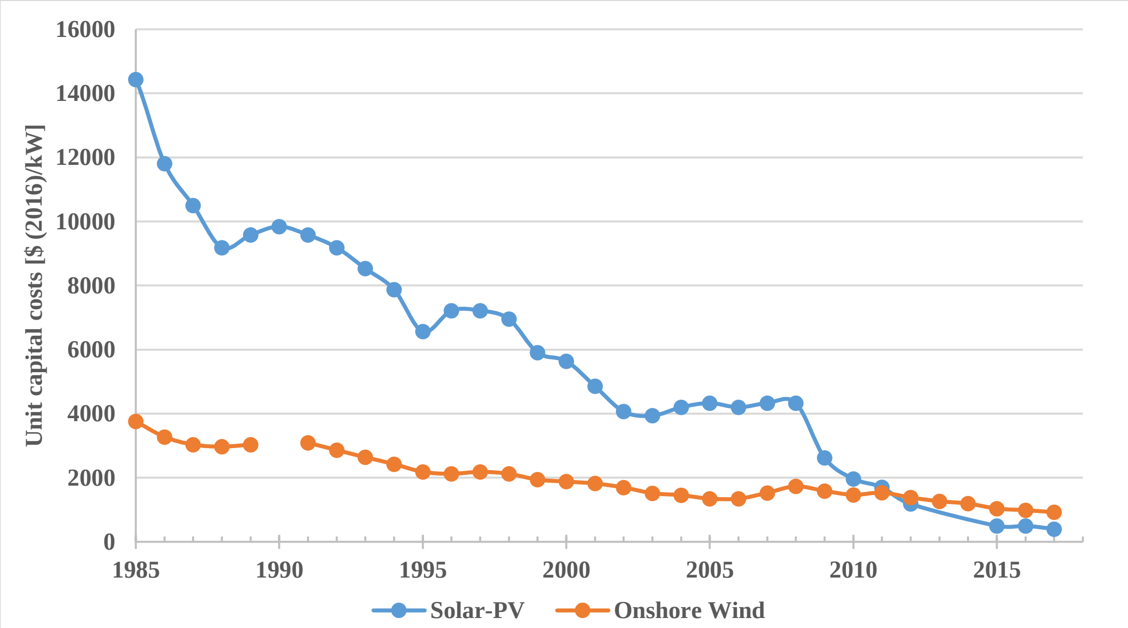


Figure 2-7. Annual average cost for solar-PV modules and onshore wind turbines. Based on: onshore wind [2, 119], solar-PV [2, 131-133].

Table 2-2 Stage of development and time period for each technology in core countries, for onshore wind e.g. Denmark and Germany, for solar-PV e.g. Japan, US, Germany. Based on: onshore wind [134, 135]. Solar-PV [97, 136-139]

Stage of development	Onshore Wind	Solar-PV
R&D stage	Until the end of 1970s	1970 to mid 1980s (moving from space to terrestrial applications)
Demonstration Stage	From the start of the 1980s (small turbines tests)	Mid 1980s- mid 1990s (off-grid decentralized, large scale plant tests)
Market formation	1980s (Californian market – small turbine plants) - 1990s (large plants applications with utilities)	End 1990s (public building rooftop integration deployment)
Full commercialization	End of 1990s (later for follower countries)	Start of 2000s (private rooftops investment programs in core countries, later around 2010 in follower countries as BRICS)

[2] Core countries are countries where innovation and development of a technology starts and the first market is deployed. For example, in onshore wind, Denmark and Germany, and for solar PV, Japan, the US and Germany are core countries. Follower countries are where technology subsequently diffuses in expanded markets.

2.5.1 Onshore wind learning drivers

MFLC analyses for onshore wind in the literature occur in the years between 1970 and 2015. Table 2-3 presents all the combinations of MFLCs investigated in the literature, listing also the different stages of development, location and important remarks. It is worth noting that moving from 1FLCs to more complex MFLCs increases the uncertainty of the results. For example, MFLCs number 14 and 16 in Table 2-3 show that adding drivers as spillover of learning (KS), demand market dynamic (DM), and economies of scale (ES) do not generate statistically significant results [24, 52, 80, 140]. In Table A-1 in appendix, more information about time periods, costs variables, driver assumptions and resulting learning rates are reported.

Table 2-3. Multi-factors learning curve developed for onshore wind, results from the literature review. Drivers' abbreviations are defined in section 2.4.

MFLC	Geographical location, technology stages, important remarks	REFERENCES
1) LBD, LBR	• Global [135, 141-144], US [145] • R&D to market formation [135, 141-144], full-commercialization [145] • LBR evaluated with both patents and RD&D expenditures in [144]. LBR rate higher impact of LBD rate in [145]	[135, 141-144] [145]
2) LBD, ES	• Global [110], India [146] • R&D, demonstration [110], full-commercialization [146] • Total annual wind power generation level parameter used to measure industrial ES	[110, 146]
3) LBD, IM-S	• European database • market formation and full-commercialization • Material prices have the highest impact in this analysis: -41% to -44% learning rate	[147]
4) LBD, DM	• South Korea [148], US [124], China [149] • Market formation [148]. Demonstration, and full commercialization [124, 149] • Two parameters are investigated for demand market dynamics, the impact of wind resource quality of different location [124, 149] and regulation and policy impact in terms of Feed-in Tariff [148], results are not significant. In [124, 148] DM are included in 1FLCs as adjustment of the other parameters	[124, 148, 149]
5) LBD, KS	• European countries (DK, DE, UK, SP) • Stages of development: Demonstration, market formation, full-commercialization • Knowledge spillover are evaluated with dummy variables for each country – to highlights the differences in initial costs between countries	[80]
6) LBD, LBR, ES	• Global • Stages of development: R&D stage and Demonstration • Total annual wind power generation level parameter used to measure industrial ES	[78, 150]
7) LBD, LBR, KS	• European countries[41, 80], Sweden [88] • Stages of development: Demonstration, market formation, full commercialization • Global LBD, and Danish LBR spillover on Sweden investment costs is measured in [88]. [41, 80] use country dummy variables spillover	[41, 80, 88]

8) LBD, ES, IM-S, DM	• US [52], India [146] • Stages of development: market formation, full commercialization (US). Full commercialization (India) • ES measured as plant capacity and unit turbine size, positive impact with the increase of plant capacity in [52, 146]. In [52], LBD shows multi-collinearity with the IM-S and cannot be measured. DM found higher prices in Californian market compared other markets, and positive impact of better resource quality on wind energy costs (capacity factor used to measure this impact).	[52] [146]
9) LBD, LBR, ES, KS	• DK, DE, UK, SP, SW • Stages of development: demonstration, market formation, full commercialization • Unit turbine size not significant, Global LBD spillover is equal to 17%.	[151]
10) LBD, KS, IM-S	• Europe • Stages of development: market formation, full commercialization • Higher impact of global LBD than national LBD (6.9% instead of 1%).	[147]
11) LBD, IM-S, DM	• India [146], Taiwan [152], US [124] • Full-commercialization [146]. Market formation and full commercialization [124, 152] • Material, plant costs impact and exchange rate variation have negative impact (IM-S) [146]. IM-S and DM, in terms of exchange rate fluctuation and wind resource quality, are used to adjust the parameters used in the 1FLC in [124]. Material prices (IM-S), oil price (DM) as interference variables in a 1FLC [152].	[124, 146, 152]
12) LBR, IM-S, KS	• Europe • Stages of development: market formation, full commercialization • Global LBR same impact of national LBR (5%) (they are merged in a single learning parameter, LBD joint LBR).	[147]
13) LBR, IM-S, KS , DM	• Europe • Stages of development: market formation, full commercialization • Regulation and policy impact (DM) found not significant.	[147]
14) ES, KS, DM	• China • Full-commercialization • KS between industrial manufactures and project developer is measured showing a low learning rate (see Table 2-5). Impact of market-pull policies (DM) is analysed: Clean Development Mechanisms, Feed-In Tariff and Local Content Requirement. Only feed-in tariff is found with significant results (LR=15%). First work including also the impact of market competition, showing the impact of wind energy deployment on the total energy demand.	[140]
15) LBD, LBR, ES, KS, DM	• European countries [80, 153], China [24] • Demonstration, market formation, full-commercialization (Europe), market formation (China) • Policy impact Feed-in Tariff measured as DM driver in [80, 153] with learning rate range between -25 to -11%. In [153] the impact of other energy type resource prices in found not significant. Country dummy variables as KS (geo) in [80, 153]. Alternative parameters in [24] to analyse LBR and KS (geo) (see more details in the discussion).	[24, 80, 153]
	• China • Full-commercialization • Comparing MFLC in number 14 the inclusion of LBD and LBR does not produce significant results	[140]

16) LBD, LBR, ES, IM-S	• China • Demonstration/market formation and Full-commercialization • Main contribution of LBD and industrial LBR, positive turbine economies of scale, negative effect of industrial economy of scale (during curtailment period), and input-prices increase weakened learning effects.	[42]

Among the MFLCs, LBD and LBR are the most frequent drivers which are discussed in the literature. Table 2-4 summarizes the LBD rates of turbine investment cost and electricity production cost in two-time periods before 2002 and after. In this way full-commercialization stages can be analysed separately from the previous stages. MFLCs for onshore wind in core countries show in general a reduced impact of LBD on costs once full commercialization is achieved, which is similar to the impact of 1FLCs (see [19]). The most recent learning curve, from 2009 to 2016 for the US, in [145] shows a 17% LBD which may show still a strong effect of this driver in US latest commercialization, while it is unlikely to be improved further in other core countries. The reduction pattern is similar in the follower countries, however, India shows a considerable higher LBD rate [146].

Table 2-4 Comparison of 1FLC LBD and MFLCs LBD in different location and time periods. Values for 1FLCs based on [19]. Analyses before 2002 indicates technology stages until market formation for follower countries. In case of core countries until the start of full commercialisation stage (see **Errore. L'origine riferimento non è stata trovata.**)

Location	Time period	LBD learning rate with 1FLC	LBD learning rate with MFLC	References
Core countries	Analysis done before 2002	Unit capital costs: -3 to 19% Electricity generation costs: 7 to 32%	Unit capital costs: 3 to 20% (Europe) 10 to 31% (Global)	MFLCs [41, 78, 80, 135, 141, 142, 144, 150, 151, 153] 1FLC [19]
	Analysis including period after 2002	Unit capital costs: 4 to 7% Electricity generation costs: 10%	Unit capital costs: 1% (Europe) 2 to 4% (Global) 17% (US) Electricity generation costs: 10% (US)	MFLCs [52, 124, 147] [145] 1FLC [19]
Follower Countries	Analysis done before 2002	Unit capital costs: 8 to 11% (Japan)	-	MFLCs [42, 140, 146, 149] 1FLC [19]
	Analysis including period after 2002	Unit capital costs: 8% Electricity generation costs: 4 to 8%	Unit capital costs: 4 to 7% (China) -11% (Taiwan) 12 to 17% (India) Electricity generation costs: 4 to 5% (China) 0.5% (South Korea) 13% to 18% (India)	MFLCs [42, 140, 146, 149] 1FLC [19]

As shown in Table 2-3, a wide number of MFLCs includes learning by-researching (LBR). When unit capital cost analysis is developed from periods of time that cover from

R&D to market formation stages, the following learning rates are found: 10-33% at a global level [78, 135, 142, 144] and 5-21% in Europe [41, 147, 151, 153]. More recent studies, covering times periods between 1991 and 2016, mostly indicate a reduction of innovation activities once commercialization is achieved, the LBR of unit capital cost is lower by 3% (at global scale) and 7 to 11% in China [42, 143]. Only the US findings in [145] show a high LBR by 37%. Instead, the LBR of unit electricity generation cost is between 4-5% [24] always in a period that cover also full-commercialization. The studies analysed use different assumptions for measuring LBR. For instance, recent analyses have used the number of patents instead of public RD&D expenditure because they better show the impact of research activities in the industry occurring during the commercialization stage [42, 154]. In [24] the parameter used is the number of turbine technologies adopted in Chinese manufactures and it represents the impact of adaptation of advanced turbine technologies. However, this study fails to distinguish between LBD and LBR because of a strong correlation between the estimation of these two parameters, this obliges to join the two drivers together in the analysis.

Economies of scale are also analysed in the literature mostly focusing on turbine nameplate scale as in [42, 52, 140, 146, 151]. Although a consistent number of studies perform MFLCs including turbine scale, only [42] shows statistically significant results with a positive return to scale rate[3] of 1.09 to 1.14 in China from demonstration to full-commercialization. Some other studies such as [78, 80, 110, 153] show a return to scale rate of 0.48 to 1.08 based on total energy generated at an industrial scale, suggesting a negative impact on cost reduction. Recent studies [24, 42, 52, 146] show a positive return to scale rates of 1.06 for the US, 1.24 for India, and average 1.13 for China based on wind farm scale, these analyses do not consider stages of R&D and demonstration.

No distinct results for learning by-using are available in the papers reviewed, while spillover of learning between actors is measured to distinguish between LBD rates for

[3] Positive economies of scale are represented with a value of return to scale higher than unity (r>1). In the case of r<1, diseconomies of scale occur because the size increase does not have a positive effect on the technology cost. In the case of r=1, the system is not influenced by economies of scale, then increasing the size does not bring any additional cost reduction.

specific type of companies and with the help of dummy variables[4]. In this way the difference of LBD rates between State-Owned- Enterprise and other company types, or new-entrants and incumbents, and big and small companies can be investigated. The spillover analysis is based only on Chinese industry both for unit capital costs [140] and for electricity generation prices [24]. In Table 2-5 shows that most of the learning rates found are not statistically significant, which could confirm that learning in China is mainly coming from the whole industry rather than from individual manufactures [24, 140]. Another important aspect of spillover is the transfer of learning between regions, particularly in case of spillover between core and follower countries. The effect of global LBD on national economies is analysed in [88, 147, 151, 153] and the key results are reported in Table 2-6. The role of Danish R&D on electricity generation costs in a small open economy such as Sweden is also investigated in [88], but with no statistically significant results. In [24], a localization rate variable is used to investigate the influence of international industry on Chinese wind electricity generation prices, this value maps the percentage of components manufactured locally compared to the ones imported. The results from the MFLCs in [24] show higher KS learning rates, between 11% to 20%, than LBD learning rates, equal to 5% which shows that an increase of components manufactured in the country reduces the cost.

Table 2-5. Learning rates of spillover between stakeholders. The results for dummy impact is a constant variable not a learning rate.

Paper	Geographical location, time period, Stage of development	Dependent variable	Spillover drivers	Learning rate	Impact of dummy variables
Model 6 from **[24]**	China 2003-2007 Early commercialization	Electricity generation cost	Whole industry cumulative capacity except the single developer	5.05%	
			Only large share developers capacity (total installed capacity > 20% of the market installed capacity)	-4.17%	
			Single developer learning	n.s.s.	
			Large share developer dummy variable		-0.46
Model 4 from **[24]**	China 2003-2007 Early commercialization	Electricity generation cost	Experience company dummy (New entry or medium size)		n.s.s.
			Business entity dummy (State owned enterprises)		n.s.s.
Model 5 from **[24]**	China 2003-2007 Early commercialization	Electricity generation cost	Experience company dummy (New entry or medium size)	n.s.s.	

[4] In dummy variable models, two binary values, 0 or 1, are used. When the data analysed has specific characteristics, the value is equal to 1 otherwise it is 0. It allows to show the difference in cost reduction between different stakeholders groups, by including or excluding nodes of data related to these specific groups.

			Business entity dummy (State owned enterprises)		n.s.s.
[140]	China 2005- 2012 Full commercialization	Unit capital costs	Single manufacture cumulative capacity		n.s.s.
			Joint cumulative capacity between project developer and manufactures	-0.6%	
			Business entity dummy both project developers and manufactures (When state owned enterprises)		n.s.s.

n.s.s. = not statistically significant

Table 2-6. Learning rates for geographical spillovers of learning.

Paper References	Geographical location	Stages of development	Dependent variable	Foreign deployment impact	Foreign research activities impact
[88]	Sweden	Market formation	Electricity generation cost	Global = 23%	Denmark = 74%
[151]	DK-UK-SP-SW-DE	Demonstration to full commercialization	Unit capital costs	Global = 17%	Europe = n.s.s
[147]	Europe	Market formation, full commercialization	Unit capital costs	Global = 1.2 to 8.4%	-
[153]	DK-UK-SP-DE	Market formation, full commercialization	Unit capital costs	-	Global = n.s.s.

The studies reviewed also show that different approaches are used to investigate the impact of supply-chain driver (IM-S). This driver is only included in the studies analysing MFLCs during the market formation and full commercialization stages. The most common approach is to measure the impact of material market prices, and the learning rates estimates show values of -56% to -31% for unit capital costs and of -18% for unit electricity generation price [24, 42, 146, 147, 152]. The negative learning rates mean that an increase of material prices increases the unit cost. Also, the impact of capital cost, another element of supply-chain input driver, is discussed for China, India and the US in [42, 52, 146]. Capital costs in these studies include plant cost indices, construction costs and interest rate on loans in five years variation, and with negative learning rates of -60% to -40%. The analysis of capital costs in these studies seeks to show how the healthiness of a national financial system impacts technology costs, and how an increase of perceived risk of investment in a country could halt the production. In addition, in [146], because of the high dependency of Indian demand on foreign suppliers, the impact of the exchange rate (Rupee/$) is also measured with a learning rate between -23 and -15%. This shows that a weakening Rupee increases the price. The review shows that the analysis of dynamics in the supply-chain driver is particularly important at country level. The material prices parameter is the only variable adopted that shows consistent estimation in the studies in the literature, but the other parameters, such as capital costs and exchange rate impact still rely on a specific case study and a general parameter is not identified.

The impact of market dynamics is also discussed in the reviewed studies. For example, in [140] the share of wind energy on the total power generated in China is used to measure the impact of an increase of market size and a learning rate of 5% for unit capital cost is found. In [152, 153] the impact of other energy resources such as the prices of oil and coal is found to be minimal. The differences between the installations in Californian market and others US markets are investigated in [52] with dummy variables. The results show higher prices in Californian markets, but the sample of data is too limited to draw strong conclusions. The impact of wind speed, measured with technology/plant capacity factor, and the market pull policies such as feed-in tariffs are discussed in [52, 80, 124, 140, 146, 148, 149]. An increase of market pull policies, as feed-in tariff or an increase of capacity factor is found to lead to higher investment costs in [80, 140] [146], negative learning rates are found from -25 to -11% in [80, 140] for feed-in tariff and equal to -40% for capacity factor in [146] or not significant in [149]. When the analysis is done using the electricity price cost metric a positive impact of capacity factor increase is found, with a learning rate from 23 to 42%, as in [52, 146]. Some analysis used these parameters as a cost adjustment parameter or a dummy variable [124, 148].

While the literature does reveal MFLC analyses, it does not reveal the application of BUCMs for onshore wind. Some engineering assessments are developed, as in [155, 156]. In these studies, the price changes of wind turbines during 2002 and 2010 in the US. The importance of drivers such as material prices, turbine scaling, labour costs and currency movements is argued, and an estimate of their variation in time is provided but a link to drivers is not directly done.

2.5.2 Solar PV learning drivers

Most of the studies of solar-PV MFLCs are at a global level, with few exceptions: one [23] focuses on Chinese PV-module, two [148, 157] focus on electricity generation costs in South Korea, and two focuses on solar investment cost one in Taiwan [158], and one in US [145]. MFLCs for technology soft costs, as installation costs, and other component costs, as inverters, are not found in the literature. Their analysis is highly influenced by local conditions due to different regulations, financial rules, installation costs and permits [159, 160]. For example, soft costs 1FLC in [159] is built for the specific case of Germany and it suggests that the inverter cost decreases by 70-87% since the 1990s, and soft costs learning curve has a learning rate of 12%.

Table 2-7.Multi-factors learning curve developed for solar-PV.

MFLCs	geographical location, technology stages, important remarks	References
1) LBD, LBR	• Global [135, 142, 143], South Korea [157] • R&D stage to market formation [135, 142], market formation and full-commercialization [143], full-commercialization [157] • LBR is based on RD&D knowledge stock, LBD is related to the cost component analysed (electricity generation costs, module costs). With the exception of the analysis done in [145], where a LBR rate equal to 66% is found, learning rates both for LBD and LBR are lower in recent analysis. 10-14% LBR rate and 17-18% LBD rate are found in in [135, 142] , while more recent works found 2-10% for LBD and 5% LBR in [143, 157]	[135, 142, 143, 157] [145]
2) LBD, ES	• Global • From R&D stage to market formation [110]. Full-commercialization [133] • The economies of industry scale measured with annual solar power generation level [110] and average annual manufacture size [133]. The results change with the different choice of parameters	[110] [133]
3) LBD, IM-S	• Global • Demonstration to full-commercialization, analysis divided by time frame • [161] found negative impact due to the increase of silicon price, in [138] results are not available. The LBD rate has a wide range from 5.2% to 21% in both two studies	[138, 161]
4) LBD, DM	• South Korea • Market Formation, full commercialization • 43% LBD rate based on cumulative electricity generated, higher than the findings from [157] in the same location and comparable area. Feed-in tariff to adjust electricity cost component in South Korea market.	[148]
5) LBD, ES, LBR	• Global • R&D stage to market formation • Both Public and Private R&D expenditures used to measure LBR in the studies LBD and LBR rates are between 1-7% range for module costs, lower that the findings in [135, 142] for comparable times periods. Economies of scale related to industry growing measured with annual power generation level are found negative confirming [110] findings.	[78, 150]
6) LBD, IM-S, DM	• Taiwan [158], global [138] • Market formation full commercialization [158], demonstration to full-commercialization [138] • Interference variables are used to adjust the 1FLC in [158]: oil price, steel, and silicon price are multiplied to the cumulative capacity. Oil price, and steel price are not significant. Silicon cost increase influence PV cost increase. In [138] imbalance between supply and demand is used, no results provided.	[158] [138]
7) LBD, IM-S, ES	• China • R&D to market formation • This MFLC shows silver market price has a positive learning rate, opposite from expected market price impact, because to the influence of material quantity.	[23]
8) LBD, ES, IM-S, DM, LBR	• Global • Full commercialization • Cumulative global capacity produced is used to measure LBD, it is found insignificant. To measure LBR silicon material use and module efficiency are used, LBR has the main impact on module cost reduction.	[133]
9) ES, IM-S, DM, LBR	• Global • Full commercialization Annual industry investment, cumulated industry investment, single firm investments are used to measure their impact on costs reduction, it	[133]

	measures a mix of LBD, IM-S (capital) and industrial DM. Annual industry investment are found to have positive learning rate and more relevant than normal LBD.

Table 2-7 shows the MFLCs for solar-PV module cost and electricity generation cost, highlighting locations, stages of development and some important remarks (more information is provided in Table A-2 in Appendix 1). LBD is the main driver explored and mostly two and three factors learning curves are developed, except [133] which investigates more than three drivers. In [23] a lot of attention is given to the impact of input materials of silicon, silver and other materials on PV cost reduction.

The studies related to MFLCs for solar-PV module costs before the end of 1990s show that LBD rates are in a range of 2 to 28%, thus excluding the full-commercialization stage (see **Errore. L'origine riferimento non è stata trovata.**) [78, 110, 135, 150]. The studies that cover the full-commercialization stage show that LBD changes from 6% to 21% [133, 138, 143, 145, 161]. Thus, the trend of LBD rate in MFLCs does not show a reduction once full commercialization is achieved.

The results for LBR show a rate of 1 to14% excluding the full-commercialization stage [78, 135, 142, 150], and 66% if only full-commercialization stage is considered in US [145]. In these studies R&D expenditures is the driver parameter. Recently [133] explores the effect of learning by-researching by using technological features parameters, the learning rate ranges between -46% to -42% with respect to material quantities parameter and it is 45% to 52% with respect to module efficiency. These use of technological feature parameters explain different learning by-researching dynamics comparing the R&D expenditures thus their learning rates cannot be directly compared. The former refers to output to innovation as the technological achievements, the latter refers to the input to innovation as funding spent in research activity.

Similar to wind energy, MFLCs for solar-PV investigate as main supply-chain driver supply material prices. The IM-S rates for China, from R&D stage to market formation, found in [23] is equal to -21.8%, 9%, and -80% for silicon, silver, and other materials, respectively. The positive learning rate found for silver shows an opposite trend comparing the silicon and other material learning rate which instead are negative, this means that even if silver market price increases the modules cost continue to decrease their prices. This is justified in [23] by the reduction of silver adoption in cells once silver market price increases but this cannot be captured in the results from the MFLC. The impact of silicon price in [133, 161] ranges between -96% and -30% when the full commercialization stage is included in the analysis.

The impact of the number of competitors in an industry is analysed in [133] as an effect of a demand-side market driver. The parameter used relates to the variation of the annual and cumulative solar-PV industry investments, and the results suggest a learning rate of 17%. This parameter is found correlated with cumulative capacity used for describing LBD, thus the two drivers cannot be separated, and LBD cannot be evaluated separately.

The results related to economies of industry scale, measured by-using an annual energy generated parameter, reveal a negative return to scale between 0.88 to 1, in the stage of R&D to the start of full-commercialization [78, 110, 150]. Instead economies of manufactures scales shows a positive return to scale of 1.07 during the same stage of development in China [23]. When the focus is only on full-commercialization stage, as in [133], return to scale of 1.54 is found for economies of manufactures scale. So, it suggests industry scale as a positive impact once the commercialization stage is reached.

Four studies develop MFLCs with different cost variables from PV module costs: two [148, 157] investigate electricity generation cost reductions in South Korea, one [142] investigates PV-project investment costs at global level, and one [158] focuses on PV-project investment costs for Taiwan. In [148, 157] the results show a 43% LBD during an early-diffusion stage and a 2% LBD during a full-commercialized stage. This huge gap in the results may be attributed to the different assumptions used in the two models. The analysis in [148] adjusts the electricity generation cost with feed-in tariff incentives (DM driver), and this justifies the higher learning found in this analysis, which is highly influenced by the demand market policy implications. In [142] a LBD rate of 17.5%, and LBR rate of 10% at global level is found, and in [158] LBD declines to 12% in a case study in Taiwan after 2000s. MFLCs reviewed rarely show the impact of other drivers. An effect of spillover is analysed in the recent work [162] where the effect of technology spillover between centralised solar PV plants and distributed applications is considered in a component-based 1FLC to evaluate the policy cost of PV support and how much the support in an application influence the other.

Two studies in the literature apply the BUCM approach for solar-PV [25, 26]. They analyse different variables and use different learning drivers. Each of these variables contribute to a certain amount of cost changes of the technology in different periods summarised in Table 2-8. Authors in [26] group LBD as the main driver for changes in yield, wafer sizes, silicon consumptions and polycrystalline shares. In [25], LBD is the main impact of yield changings and it is argued that changes of wafer area and silicon usage, which are mainly driven by LBR, could be also influenced by LBD. Both [25, 26] suggest that LBR influences the improvement of technology efficiency. In [26] silicon price is considered as an independent variable driven by spillover from microprocessor industry which were the main demand consumers of purified silicon until 2001. The same assumption is used in [25] for the analysis until 2001, while the driver associated to silicon price after 2001 is the economies of scale. Economies of scale are associated also to module plant size both in [25, 26]. As show in Table 2-8, learning by-doing is the least impacting driver on cost reductions in the whole periods analysed. During the first period, 1980-2001, in [26] module efficiency, silicon costs, and manufacture plant size are the main variables that impacted the cost reduction. While in [25] these variables are the module efficiency, silicon cost, and silicon usage. During the second period, 2001-2012, manufacturing plant size and wafer area and module efficiency are the main variables [25].

Table 2-8. Results for BUCMs for PV-modules.

Paper References	**Independent variables**	**Costs changes ($/W)**	**Time period**
Learning by-doing			
[26]	Yield - y = 88% → 92%	-0.43	1980-2001
[26]	Silicon utilization u=28 g/W → 18 g/W	-0.62	1980-2001
[26]	Wafer Area - A= 45 cm^2 → 180 cm^2	-0.67	1980-2001
[26]	Poly-crystalline share =0% → 50%	-0.38	1980-2001
[25]	Yield y = 75% → 86%	-1.73	1980-2001
[25]	Yield y = 86% → 95%	-0.21	2001-2012
[25]	Yield y = 75% → 95%	-1.95	1980-2012
learning by-researching			
[26]	Module efficiency - η = 8% →13.5%	-6.5	1980-2001
[25]	Module efficiency η = 8% → 13%	-5.96	1980-2001
[25]	Silicon usage v = 0.25 cm → 0.083 cm	-3.8	1980-2001
[25]	Wafer Area = 90 cm^2 → 156 cm^2	-2.71	1980-2001
[25]	Module efficiency η = 13% → 15.2%	-0.35	2001-2012
[25]	Wafer Area = 156 cm^2 → 243 cm^2	-0.48	2001-2012
[25]	Silicon usage v = 0.083 cm → 0.04 cm	-0.23	2001-2012
[25]	Module efficiency η = 8% →15.2%	-6.3	1980-2012
[25]	Wafer Area = 90 cm^2 → 243 cm^2	-3.19	1980-2012
[25]	Silicon usage cm = 0.25 cm → 0.04 cm	-4.02	1980-2012

Spillover of learning			
[26]	Silicon costs - Si = 131$/kg → 25$/kg	-2.67	1980-2001
[25]	Silicon cost Si = 126 $/kg → 36 $/kg	-4.38	1980-2001
Economies of scale			
[25]	Manufacturing plant size = 1MW/yr →13.3 MW/yr	-2.07	1980-2001
[26]	Manufacturing plant size = 125 kW/yr →14 MW/yr	-9.22	1980-2001
[25]	Silicon costs Si = 36 $/kg → 26 $/kg	-0.1	2001-2012
[25]	Manufacturing plant size = 13.3 MW/yr →1000 MW/yr	-1.08	2001-2012
[25]	Manufacturing plant size = 1MW/yr →1000 MW/yr	-3.15	1980-2012

2.6 Summary of cost drivers differences with the two methods

This literature review summarises which drivers cause the cost reductions in wind and solar-PV in the past. Table 2-9 provides a summary of the findings in case of unit capital costs for comparing the studies. It is clear from the review that not enough studies have analysed drivers such as supply-chain and demand-side market spillovers of learning and still there is not uniformity in the driver variables used and thus on driver finding, moreover, no study has investigated the impact of learning by-using. The BUCMs results provide some additional indications about the impact of drivers and main techno-economic variables responsible for cost changes, which increase our understanding of changing cost dynamics for solar-PV.

Interestingly, the two methods, MFLCs and BUCMs, are not always in accordance with the drivers which influence solar-PV cost reductions. The impact of LBD at full-commercialization stage is observed for MFLCs, but not seen for BUCMs. Moreover, in depending on the technology stages, silicon prices have different drivers impacts in BUCMs. At earlier stages they are considered as a knowledge spillover driver from other industry and with high impact, whereas during full commercialization they act like an economy of supply-chain scale with low impact. By contrast, the silicon price has a high impact in MFLCs along all stages of development, particularly when full commercialization is achieved. The economy of industry scale during the earlier stages of development is mostly negative or with a low positive effect in MFLCs, while it is the main driver of cost reduction in BUCMs before 2002. Regarding later studies of MFLCs covering period after 2002 show that then the contribution of manufacturing scale increase.

Beside the general driver comparison, the two analysis produce different outputs; learning curves inform on the percentage of cost reduction if double the parameter used to investigate the driver, such as deployment capacity, R&D investment, plant size; while on the other side, BUCMs show the absolute value in cost reducing, in $/kW, and it is dependent on the years used to perform the investigation. Both of them perform useful insights and their results can contribute to the understanding of drivers impact on cost reduction.

Table 2-9. Summary of drivers impacting different stages of development for on shore wind and solar PV according to literature review.

Energy Type	Drivers till market formation (before 2000s)	Drivers in full-commercialization (after 2000s)
WIND	LBD: High impact (3-31% LR global) LBR: High impact (10-33% LR global) ES: Mostly diseconomies of industry scale KS: Technology and industry spillovers of learning from core countries to close follower economies (DK to Sweden LBR=74%, Global to Sweden LBD=23%)	LBD: Reduced impact (1-10% LR global) LBR: Reduced impact (3% LR global) ES: Stronger economies of scale at device level, and wind farm size KS: Technology spillovers from core countries to global follower economies (China 11-20% KS rate) IM-S: Material prices, capital costs and exchange rate high impact than LBD and LBR. National financial healthiness may drive cost changes locally DM: A stable regulation and policy in favour of wind installations and market expansion and penetrations reduce costs (ex. 5% LR market expansion in China)
SOLAR-PV	LBD: MFLCs: High impact (2-28% LR global) BUCMs: High impact of process yield (-1.73$/KW) LBR: MFLCs: Relevant learning (1-14% LR global) BUCMs: High impact of module efficiency (-5.96/-6 $/KW) and silicon usage (-3.8 $/kW) IS-M: MFLCs: Highest impact of materials prices in influencing costs KS: BUCMs: Semiconductor industry market is the main user of silicon at earlier stage than its price for this market is influencing Solar-PV costs. Effect of industry spillover on silicon cost (-4.38/-2.67 $/kW) ES: MFLCs: Diseconomies of industry scale	LBD: MFLCs: Relevant impact (6-21% LR global) BUCMs: Minor evidences of this driver (-0.21 $/kW) LBR: MFLCs: Relevant impact of this driver in technology characteristics (research breakthroughs helped to reduce material quantity and to increase module efficiency, LR material quantities = -46%/-42%, LR module efficiency = 45/52%) BUCMs: main driver of cost reduction at this stage, Wafer area (-3.19 $/kW), silicon usage (-4.02 $/kW) IS-M: MFLCs: Relevant impact of supply-dynamics related to material prices (silicon price LR =-96%/-22%) BUCMs: not included in this category but instead as economies of scale. ES: MFLCs: Relevant industry economies of scale BUCMS: plant size increase is impacting in cost reduction (-1.08 $/kW). Silicon price is considered an economy of scale effect after 2001 with low impact (0.1 $/kW)

	BUCMs: Main positive driver of cost reduction (-9.22 $/kW)	DM: MFLC: Relevant impact of industry investments on cost reduction, used to measure market expansion and global industry competitions (LR=17%)

2.7 Conclusions and recommendations

The role of energy technology innovation is recognised as having a strong role in achieving renewable energy technology cost reductions. Our review reveals both the level of current understanding, and the limitations, in quantifying the impact of energy technology innovation.

A review on the framework of energy technology innovation impact on cost reduction in section 2-4 shows how the role of drivers change with the developmental stage of technology. Learning by-doing, learning by-researching and spillover of learning are important drivers at the earlier stage of development. In the commercialization stage, the preeminent drivers are demand market, supply-chain dynamics and economies of scale. Thus, this shows that it is important to identify which driver is contributing to learning at different stages of development for each technology in the past to avoid producing misleading conclusions about future cost reductions.

We also noted that the most common quantitative tool to measure cost reduction is 1FLC which may ignore the effect of many drivers affecting the cost reduction of energy technology innovation. We noted that in the last two decades advanced methods to analyse multiple drivers have become widely used in the literature to enlarge the understanding of cost reduction. The resulting learning rates vary according to the type of MFLCs used, data and assumptions of variables, locations and time periods. This review provides a detailed overview of drivers that impact the cost reduction of wind and solar-PV in their stages of development. This review finds that most of the suggested learning drivers discussed qualitatively in the literature are still not properly described quantitatively. Quantifying demand market dynamics, learning by-using and knowledge spillovers are poorly analysed because of the difficulty identifying robust parameters for statistically significant and uncorrelated results.

In addition, the findings from BUCM papers are also reviewed. This methodology presents cost reductions with a different metric from learning rate and shows the influence on technology cost changes of a variable in a specific time-period. The results for solar-

PV suggests that the application of BUCM would deepen our understanding of the technical variables influencing cost reductions. This method tries to reduce the uncertainty behind the issue of correlation between the parameters used to measure drivers and costs in learning curves and links drivers with quantifiable variables. On the other hand, the methodology does have some limitations and insufficient analyses to overcome the analytical issues or assumptions. A summary of impact of drivers for these two technologies along the stages of development were presented in section 4.3.

As per our knowledge, this is the first review to scrutinise the results from the literature on multiple drivers and to discuss the importance of these drivers along the stages of development. It responds to recommendations from previous review papers that call out the need to include more drivers in cost analyses [16, 18, 19, 70]. This review clarifies the current understanding of the impact of energy technology innovations on cost reductions. More research on multiple drivers that influence technology innovations is needed to support the policy. There are multiple areas where additional research is required. First, investigating more energy technologies using more diversity in geographical areas. The assumption of global or local data must be further investigated in the research field to allow investigating the drivers correlated with the market development and geographical spillovers. Second, both MFLCs and BUCMs analyses should be used to explain the underlying drivers governing energy technology innovations and, therefore, reduce the current uncertainties in the results. Third, analysis of drivers is required at different stages of development to show how cost reduction drivers vary in their development stages and which characterizations of the energy technology innovation system are most significant. An integration with innovation studies could contribute to feed the gap where there is a lack of data availability. Moreover, energy technology innovations not only influence renewable energy technology costs but also have an impact on energy diffusions and on improving the associated technical performance. Clarifying the role of the drivers from the aspect of technological changes, as done for example in [140, 163, 164], would increase the comprehensive understanding of technology innovations. Furthermore, it would enable more robust assumptions related to the technology innovation impacts in long-term optimization energy system models, the main tool used to discuss the energy policy implications.

Chapter 3

Wind energy cost reduction: a detailed bottom-up analysis of innovation drivers

3.1 Abstract

Wind energy technology has seen a rapid decline in costs in the last three decades but the precise reasons for these cost reductions are poorly understood. This chapter addresses this knowledge gap by quantitatively investigating the reasons behind the cost reductions between 2005 and 2017. The purpose of this chapter is to deepen our understanding of what drives these cost reductions. Initially, we develop an advanced bottom-up cost model and use this to quantify the individual cost components of the wind turbine. The chapter also identifies the associated techno-economic variables responsible for specific cost changes. We then link these individual cost reductions to innovation drivers identified in the literature, specifically learning by-deployment, learning by-researching, supply-chain dynamics, and market dynamics. The findings show that material, labour, legal and financial costs are responsible for 41-52% of wind turbine costs yearly, and 31% of wind turbine cost reductions in the period analysed. These specific costs reductions are directly linked to techno-economic variables, principally the reduction of copper, fiberglass and iron, and increased employee productivity. These variables point to learning by-deployment as being the most important innovation driver, but also reveal a contribution from supply-chain and market dynamics.

3.2 Introduction

By the 1970s governments had already started to invest in wind energy R&D as a cost-effective solution to the energy security challenges of the oil crisis; later, in the 1990s, further investment was made in the name of low carbon development. Nowadays, wind energy is a longstanding renewable energy technology which has been successfully deployed, mostly in an onshore setting. At its current stage of development wind is considered a mature technology, fully commercialised in western countries with a stable and structured industry, and with increasing market expansion in emerging economies such as China and India [165]. Technology cost reduction is an important attribute responsible for wind technology innovation. In Germany, in 2018, wind energy LCOE was lower than conventional fossil fuel technologies [166], and globally it reached values below 0.1 $/kWh (in constant 2016$)[2]. In 2017, the total wind energy installed reached 540 GW worldwide, providing 5% of the total electricity generated [165]. In order to foster these least-cost pathways that include renewable energy technology it is important to understand the drivers of renewable energy technology cost reduction. For this information to be most useful to policy makers, it needs to identify not only the order of magnitude of total cost reductions (e.g. in terms of specific cost in USD/kW or USD/kWh), but also which cost categories (e.g. materials, manufacturing, labour) contributed the largest share and furthermore what are the main underlying drivers of those cost reductions in terms of learning effects (e.g., learning-by-deployment, learning-by-researching, etc.).

Recently, an expert elicitation survey on future energy wind costs underlined the uncertainties behind future costs reduction for energy generated from wind, and gives an idea of the expected order of magnitude of total cost reduction in the future [167]. Instead, in this research we examine the price of wind turbines in the last 12 years (2005 – 2017) with an advanced bottom-up cost model which evaluates technology cost reduction, disaggregating it into different cost components and identifies with a cost equation quantifiable variables responsible of these cost changes. In this way it is then possible to link cost components with the drivers of cost reduction. This analysis tries to reduce the current knowledge gap on the causal relationship between cost reductions and the drivers of cost reduction, a gap which is usually investigated with experience curves albeit with limitations [16]. Previous analyses investigating drivers of cost reduction with advanced bottom-up cost model focussed on solar-photovoltaics and coal fired plants [25, 26, 77].

While previous cost component disaggregation analyses on wind energy have been done, as in [155, 168], these analyses didn't describe a link between cost reduction and the underlying drivers, which remains a knowledge gap in the literature.

This chapter aims to identify the contribution of four drivers, namely learning by-deployment, learning by-researching, supply-chain dynamics, and market dynamics. The drivers represent general system dynamics occurring along the stages of development of a technology which results in technology cost reduction. Using the approach shown in Figure 3-1 the impact of each driver can be associated to specific quantifiable techno-economic variables which explains cost reductions for each cost component. For example, material costs components are linked with material market price which is then associated to supply-chain dynamics driver. This new method requires appropriate data to work and the best data available from Vestas and NREL cost analysis reports are used in the analysis [168-170].

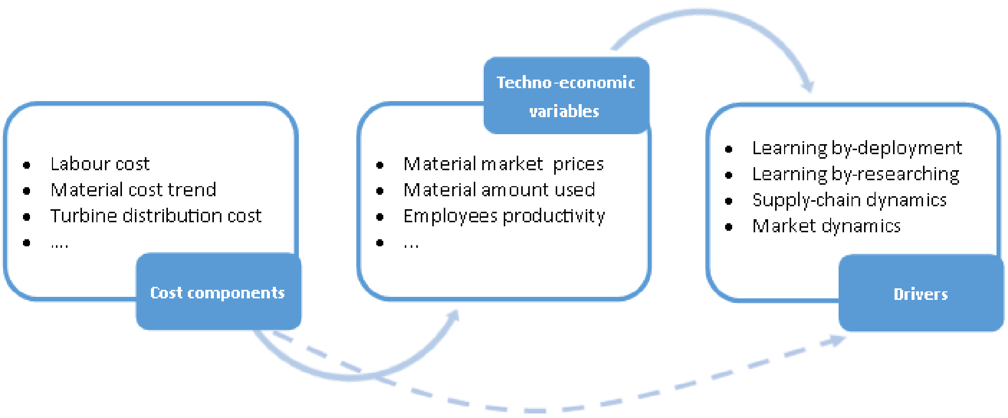


Figure 3-1. Model framework used in the chapter. The list of cost components and techno-economic variables in this figure is partial. The dashed-line connects cost components to drivers when data about techno-economic variables are not available

The chapter is divided as follow: section 2 outlines the three main methodologies used to analyse cost reduction dynamics in the literature. Section 3 describes the methodological approach used in this chapter. In section 4 the data assumption and cost components evaluation are described. In section 5 the results and discussion are reported. Section 6 concludes drawing insights from the analysis.

3.3 Understanding cost reduction dynamics

The most widespread tool used to investigate the drivers of costs is based on correlation between costs and capacity installed, namely defined as one-factor learning curve (1FLC). 1FLC implies deployment-induced learning as only driver of technology cost changes, and this high level aggregation does not allow a deeper understanding of the different cost drivers [19]. Advanced forms of experience curves, named multi-factor learning curves (MFLC), investigate macro drivers as learning by-doing, learning by-researching, economies of scale [23, 24, 42, 140] (results for onshore wind in Table 3-1). For example, two-factor learning curves have been used in the literature to compare the impact of market stimulation policies and technology-push stimulation policies, by using parameters such as cumulative capacity and R&D expenditure [80, 153]. MFLCs attempt to understand the mechanics of technology cost reduction by using general system parameters, but most of them fail to include techno-economic features, such as the impact of the physics of devices or manufacturing processes. Some MFLCs include material market price and technology size in their formula to investigate the impact of the market of supply and economies of scale [24, 42, 154], but adding additional drivers arise new uncertainties in the model due to the statistical correlation between multiple variables. This has pushed scholars towards merging some drivers in order to avoid poorly correlated results [24, 154].

Recent analyses [25, 26, 77] have started to develop advanced bottom-up cost models (BUCM) which are used to disaggregate technology costs in its costs components and project future costs based on expert opinion [53, 171, 172]. In addition to a simple bottom-up approach, this advanced method quantifies how much each cost component impact on technology cost reduction, for example how much material, capital depreciation, labour impacts on technology costs. Likewise, in BUCM, a cost equation allows to identify the role of techno-economic variables for each cost component. The variables are quantifiable metrics in the system such as material quantity, material price, and employees' productivity. The use of these methods enables to link the drivers with quantifiable metrics instead of basing cost reduction trends on conceptual drivers linked with proxy parameters [25, 26, 77].

The main challenge in this approach, which can yield greater insights, remains the higher data requirements. This new approach requires the population of a cost equation for each technology and the level of detail is often limited by data availability, thus this method is not exonerated by uncertainties related to modelling assumptions. Moreover, BUCM implicitly assumes that the variables used in the cost equations are independent and not correlated, this a priori assumption is adopted to avoid the risk of correlation between the variables in the equation but might not always reflect reality, for example innovation in reducing material usage could be pushed both by material market price, learning by-researching and learning by-deployment [23].

While experience curves are the main method used to analyse drivers of costs reduction still the results are uncertain. With BUCM the relationship between cost and drivers is stepping out from identifying econometric correlation allowing a more robust understanding. Moreover, experience curves perform better with a long series of data, thus the analysis in short time period is limited which instead can be evaluated with BUCM showing cost changes at different stages of development of the technology.

Table 3-1. Comparison drivers impact with results in from the experience curve literature (in this table economies of scale are included in the other drivers to compare with the BUCM results in this chapter)

Drivers		**Learning rates results only for analysis done after 2000 and with capital costs variables (thus electricity cost results are not summarised here)**
Learning by-deployment	Learning by-doing (cumulative capacity)	Western countries: 1% (EU) [147] , 10-17% (US) Global: 2-4% [143] China: 4-9% [42, 140, 149] India: 12-17% [146]
	Knowledge Spillover	Scattered results for China using dummy variables Joint learning for project developer and manufacture:-0.6% [140]
	Manufacturing economies of scale	-
Learning by-researching	Learning by-researching (RD&D expenditures)	Europe: 5% [147] China: 4-11% [24, 42] Global: 3-4% [143]
	Device economies of scale	Turbine nameplate return to scale range: 1.09-1.14 [42] Wind farm size return to scale: 0.91-0.96 [42]
Supply chain dynamics		Steel market price (or indexes) learning rate: -44% to -28% [24, 42, 147] Exchange rate (impact of supply imported in India): -23% to -15% [146]
Market dynamics		Different parameters investigated: Policy implications: Feed-in tariff impact – 25% to -11% [80, 140, 153] Market expansion: wind capacity in the market 5% [140] Market quality: Capacity factor -40% [146]

3.4 Methodology

We used the BUCM approach to understand what drives cost reduction. In section 3.1 the cost equation to describe wind turbine prices is developed to estimate each cost component in the period selected (Figure 3-2, Eq. 1). Then the link with drivers is described in section 3.2.

3.4.1 Cost decomposition equation

Wind turbine price is disaggregated into its cost components in Figure 3-2. This model, based on the most robust data available, allows analysis of wind turbine prices at different levels, considering cost components and the impact of techno-economic variables. The cost equation used to describe wind turbine price C_{wind} is described as follow:

$$C_{wind}\left[\frac{\$}{kW}\right] = \sum_{i=1}^{m} Q_{Mi}\, P_{Mi} + \sum_{j=1}^{n} Q_{Ej}\, P_{Ej} + \varepsilon_{lab}\, WAGE + C_{capital} + C_{Turbine\,distribution} + C_{installation} + C_{R\&D} + C_{legal\&financial} + C_{suppliers\&residual} + C_{company\,profit} \quad (1)$$

The first three cost components represents the cost of materials, energy consumption and labour and the techno-economic variables identified are: Q_{Mi} the quantity of materials per kW produced, P_{Mi} the price of materials, Q_{Ej} the energy consumption per kW produced, P_{Ej} the price of energy, ε_{lab} the employs' productivity per kW produced, and $WAGE$ the average annual manufacture salary. The residual part is decomposed into the following costs components: $C_{capital}$ includes the value of property, plant and equipment, while $C_{turbine\,distribution}$ includes the costs to provide transport of turbine to the site, $C_{installation}$ are related to costs of installation and together they are defined as $C_{delivery\,cost}$, $C_{legal\&financial}$ related to the insurance and financial construction costs, $C_{R\&D}$ are part of the operating costs in a manufacture, $C_{suppliers\&others}$ includes the cost of suppliers when components are bought and not produced, and any not-accounted cost in the previous categories. Last component $C_{company\,profit}$ is dependent from the relationship between production and demand, and the company market strength. These components are further modeled and described in section 4, and Appendix B provides more details.

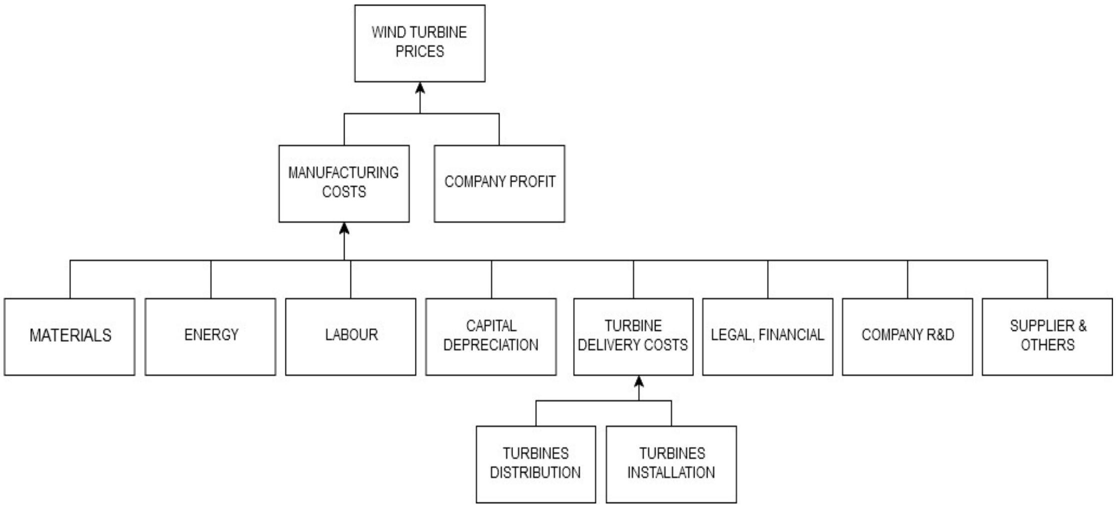


Figure 3-2. Wind turbine price decomposition in cost components as analysed in the chapter

3.4.2 Attributing cost changes to drivers

In this analysis the drivers considered are learning by-deployment, learning by-researching, supply-chain dynamics and market dynamics. Learning by-deployment relates to achievement in the manufacture which includes also the knowledge exchanged between companies and with customers (formally spillover) [19]. It also includes manufacture scale, as the advantages to adopt bigger equipment with the increase of manufacture size, or cost saving obtained thanks to purchasing of bigger material stock from a supplier. Learning by-researching relates to lab and not productive activities [47, 105], including the achievements reached at device size scale as increasing turbine nameplate, rotor and tower size. External to manufactures and research cost changes are considered under two categories supply-chain dynamics or market dynamics. The first includes dynamics related to the market of production as the variation of material and supply prices or the availability of suppliers industry, the second relates to the demand-side dynamics as the variation of competitors in a market, or variation of regulation between different markets [119].

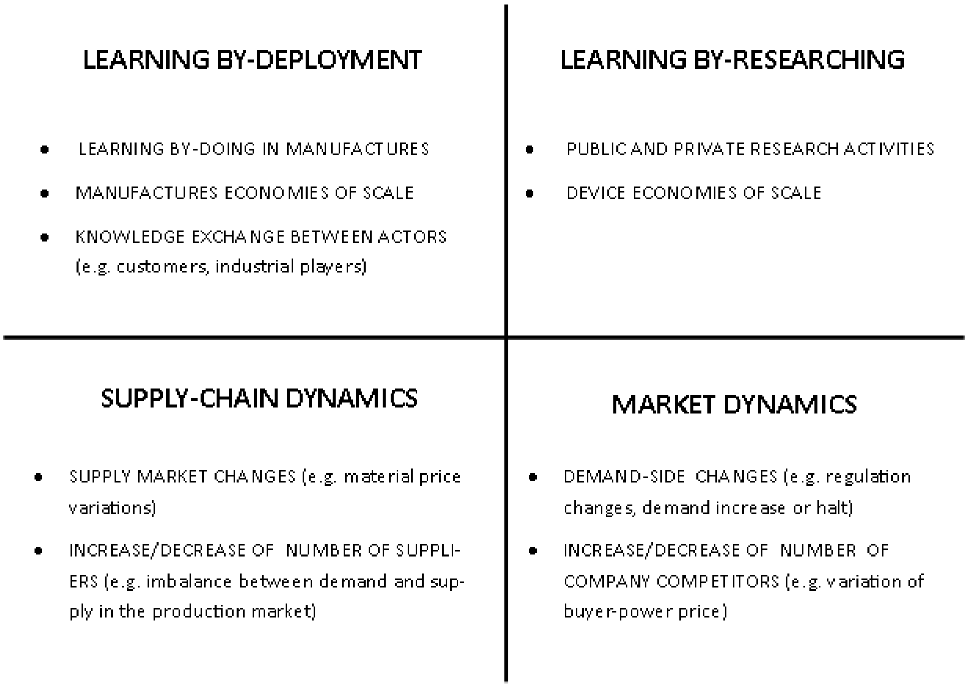


Figure 3-3. Concept drivers group categories used in this chapter

In the case of material, energy and labour cost components two techno-economic variables are associated to each of these cost components. In this way it is possible to separate the contribution to cost reduction of different drivers associated to the same cost component with a higher level of robustness avoiding qualitative assumptions for these cost components. The contribution of each techno-economic variable (Table 3-2) to total wind turbine prices is evaluated applying a method based on the finite differential (Δf(x,y)) of a function C_i= f(x,y)=xy (based on [77], details in Appendix B).

Once the wind turbine price is disaggregated in all its contributions, each cost component is linked to the drivers according to their impact (Figure 3-3). These links are further described in Section 4.9.

Table 3-2. Data used to calculate the disaggregated costs components.

Costs components	Techno-economic variables	2005	2008	2017
STEEL PRICE	Market price [$2016/ton]	737	1014	592
	Quantity [ton/kW]	0.11	0.08	0.13
FIBERGLASS	Market price [$2016/ton]	1780	1493	929
	Quantity [ton/kW]	0.0097	0.0041	0.0078
CONCRETE	Market price [$2016/ton]	141	129	122
	Quantity [ton/kW]	0.55	0.33	0.46
CAST IRON	Market price [$2016/ton]	877	1112	1109
	Quantity [ton/kW]	0.02	0.0108	0.0133
ALUMINUM	Market price [$2016/ton]	2581	3205	2121
	Quantity [ton/kW]	0.0132	0.00323	0.0051
COPPER	Market price [$2016/ton]	5001	8663	6651
	Quantity [ton/kW]	0.00328	0.00213	0.0017
POLYMERS	Market price [$2016/ton]	1873	2024	2120
	Quantity [ton/kW]	0.0042	0.0033	0.0065
ELECTRICITY	Electricity price [$2016/kWh]	0.147	0.167	0.115
	Electricity consumption [kWh/kW]	50.86	50.43	41.19
THERMAL ENERGY	Thermal energy price [$2016/kWh]	0.041	0.067	0.027
	Thermal energy consumption [kWh/kW]	21	32	24
LABOUR COSTS	Employees productivity [employees/kW]	0.0033	0.0037	0.0027
	Salary [$2016/per employee annum]	67926	72432	68977

3.5 Data

This section evaluates all the cost components and respective techno-economic variables analysed in equation 1, and it sets the assumptions to evaluate the drivers' impact.

3.5.1 Material costs

Material cost component includes all the amount of materials used in a wind turbine tower, nacelle, blades, hub and foundations and can be expressed as in equation 2. Steel is used in tower, gearbox and inside nacelle; fiberglass and resins are used in rotor blades, rotor hub and as nacelle cover; different polymers, cast iron, copper and aluminium are used inside nacelle, rotor hub, and for balance of the system components as transformer, switch gear, and site cabling. Turbine foundation are composed mainly of concrete and steel. In our analysis related materials are aggregated on single categories (e.g. steel includes alloyed and unalloyed steel) and electronics and lubricants are not included, they account for less than 1% of total mass turbine, including also balance of the system components, and it is difficult to evaluate their cost.

$$Material\ costs\ \left[\frac{\$}{kW}\right] = \sum_{i=1}^{n} Q_{Mi}\left[\frac{ton}{kW}\right] \cdot P_{Mi}\ \left[\frac{\$}{ton}\right] \cdot \qquad (2)$$

The techno economic variables considered are Q_{Mi} as the quantity of material i for kW and P_{Mi} as the market price.

Historical market prices for materials are based on statistical database [173-175] when an absolute value is not available for all the years a producer price index have been used. Data used for material amount are based on Vestas turbine models [169] and their values are compared with studies in the literature [176, 177]. The amount of material is provided for each type of turbine but not for each turbine component, such as tower and blades. The material quantity is linked with turbine characteristics as nameplate size, tower and rotor length, steel material shows some negative economies of scale with the increase of nameplate size particularly for turbines above 3 MW. The economies of scale are tested in Appendix B applying the method used in [43]..

The annual data on material quantity are based on the most grid connected turbine in each specific year, based on dataset of turbines available from Vestas. Moreover, considering that a turbine has a lead-time of maximum 2 years from the planning to the installation [178, 179], and materials are bought at the start of turbine manufacturing which requires between 3 to 6 months, materials bought and turbine production are assumed occurring in the same year. These assumption are considered more accurate than previous assumptions done in [155], where one turbine model is used as a reference for the whole period taken in the analysis missing to show the impact on cost of technical improvements and economies of scale. In 2005 the most installed turbine is V80 – 2MW, in 2008 V90 – 2 MW and in 2017 V110 – 2 MW (details in Appendix B of this thesis).

3.5.2 Energy cost

Energy costs include energy required in a manufacture to build wind turbines, they can be written as in equation 3, where Q_{Ej} is the contribution of type of energy required per kW turbines produced, both thermal energy and electricity, P_{Ej} is the energy price in the market.

$$Energy\ costs\ \left[\frac{\$}{kW}\right] = \sum_{i=1}^{n} Q_{Ej}\left[\frac{kWh}{kW}\right] \cdot P_{Ej}\ \left[\frac{\$}{kWh}\right] \qquad (3)$$

Combining the data about required primary energy consumption reported in [180] and the energy consumption for specific energy resources in [169], it is possible to evaluate the electricity and thermal energy needs required in the turbine life-cycle. Within the not-renewable resources natural gas, crude oil and coal contribute to thermal energy production, moreover, natural gas and crude oil are also used as material constituents (e.g. to produce plastics), and nuclear is used to produce electricity. Within the renewables (RES) it is assumed that wind energy, hydropower, solar produce renewable electricity and biomass for heating. We assumed the share of energy resources in each category RES-electricity, RES-other and NOT-RES based on the information gathered in [169] and contribution to produce thermal or electricity along all the period of the analysis based on [181] (Table 3-3).

Table 3-3.Energy resource assumptions by energy type

Energy type	**Fuel share per type**	**Contribution to produce thermal energy**	**Contribution to produce electricity**
Not-RES			
Oil	40%	100%	0%
Natural Gas	32%	62%	38%
Coal	20%	0%	100%
Uranium	8%	0%	100%
RES-electricity			
Wind	75%	0%	100%
Hydro	25%	0%	100%
RES-others			
Biomass	100%	100%	0%

Average industrial electricity prices per the European market are used for the electricity costs [175] and data based on [181, 182] are used to evaluate thermal energy prices (see Appendix B for more information).

3.5.3 Labour costs

Labour cost component should decrease with the increase of experience in a manufacture, as workers increase their competences and a more efficient lean production and management develop [83, 94]. Labour costs is also driven by salary price variation (Eq. 4)

$$Labour\ costs\ [\$] = \sum_{i=1}^{n} WAGE\ \left[\frac{\$}{employ}\right] \cdot \varepsilon_{lab}\ \left[\frac{number\ employees}{kW\ produced}\right] \qquad (4)$$

We model labour cost basing on Vestas data about staff costs and the number of employees [170]. It is worth to noting that Vestas revenues do not come only from the wind turbine selling but also from additional services provided, as turbine distribution, installation, site preparation, or complete turn-key plants. Moreover, after 2012, Vestas include in its business services regarding the O&M in operative power plants. In this chapter labour costs are related to the whole company services, including also distribution, R&D employees and administration; the methods used to account the staff costs and number of employees for each departments vary in the annual financial reports, thus, it is not possible to isolate each department contribution.

It is established that Vestas staff salaries are higher than in other manufactures (Figure 3-4), data taken from financial report of Suzlon [183], and Siemens-Gamesa [184] are used as comparison. Possible explanation is addressed to the range of salary from lower to qualified jobs and from manufacturing to service jobs in the dataset available, indeed Vestas cumulative investment of R&D hit 2.2 billion $ which is way over the amount invested from other companies as Goldwind [36], this makes things that more labour expensive environment are accounted in Vestas comparing other industry (technology innovation is still lead by Vestas) . Moreover, the values are based on kW delivered and not on the manufacture annual production capacity, the labour cost values may show less spikes if the capacity utilization of Vestas manufactures were available [185].

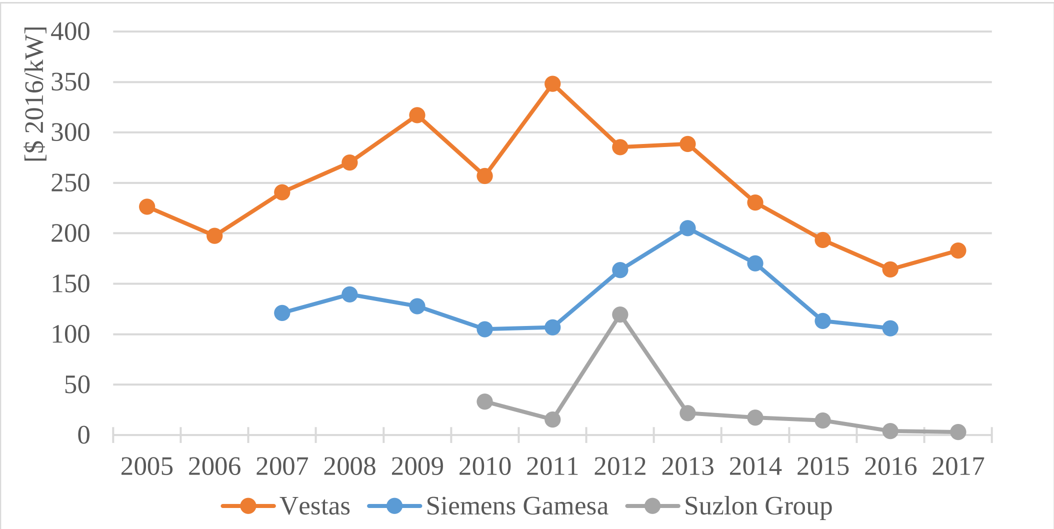


Figure 3-4. Labour cost different manufactures

3.5.4 Depreciation of capital costs

The production of a turbine requires to invest in property, plant and advanced manufacturing equipment. Growing the scale of production in a manufacture increase the amount of equipment required, and increasing the size of turbine also requires more innovative equipment [186]. The advantageous economies of scale contribute to reduce cost per kW produced in long term period [187], thus it is expected this cost component be driven by learning by-deployment and manufacture economy of scale.

To model the impact of this cost component the capital depreciation parameter is used, which measures the loss of value of equipment and facilities due to the use and the life span [188]. Data of capital depreciation are base on Vestas financial report [180]. This parameter does not represent 100% the expenses to buy a new equipment but it can be interpreted as annual amortization of equipment and facility bought, thus as the annual payment if borrowed funds would be invested for constructions [77].

3.5.5 Turbine delivery costs

Nowadays delivery services, both distribution and installation, are provided by manufacturers when a wind turbine is purchased. Data in this analysis are based on [180] and shows that turn-key projects still represent a small portion of the revenues, 8% of the revenues in 2017, thus their revenues do include transportation and installation costs but not grid connection cost, therefore these are excluded in this analysis.

Delivery costs are driven by capital cost of equipment for delivery operations, owned or borrowed, and the time required to install turbines [189, 190]. The decision to use larger equipment may increases capex costs but it could reduce the time required and, thus, the relative costs of labour, permits, and leasing. The choice of larger equipment depends on the project or turbine size and from the transport infrastructure in the country, thus they are project based. Positive economies of scale means that when increasing the turbine size does not bring to additional time and cost, above this optimum value, any bigger size requires more expensive transports or time [23, 191].

It is expected that equipment for delivery become optimized at least costs during each stage of development, proportional and adapted to the current size of a technology and the individual market. Moving to bigger size of turbines requires to investigate innovative solutions to avoid the increase of delivery costs with device scale. In a long-term period delivery costs vary mainly with company scale and management experience, reaching full-commercialization stage the manufacturers tend to move to developing countries to reduce their own costs of production or to delocalize in new demand markets [83].

Figure 3-5 shows distribution cost for Vestas from 2005 to 2017 compared with the number of employees and deliveries in the main markets. It can be observed that in 2005 the production was mostly concentrated in European continent. During 2008-2017, the wind market raised with global expansion, in the case of Vestas the capacity delivered in the Americas in 2017 almost reached the size of the European market. Most of the production departments moved to cheapest markets as Brasil, China, India, and new services and sales department developed in the demand markets as US, South America and European countries. The consolidation in new markets endured the interaction with local supply chain contractors, alignment with local policies and better company management which lead to and distribution cost decrease after 2008.

Thus, it is expected distribution costs differ for different markets according to their proximity to the manufactures production site and to the accumulation of experience in the industry about services management. Moreover technical improvements as bigger size equipment that better adapt to bigger size turbines, also contribute to turbine delivery cost changes [189]. Turbine distribution cost changes can be modelled by using Vestas distribution costs in the financial reports, they include the costs to deliver the product at the installation site. Installation costs assumptions are based on NREL report [168] which provides already provide the share of impact of this cost component on total wind turbine prices. Because absolute values are not available, with this less robust assumption a techno-economic variables disaggregation is not possible.

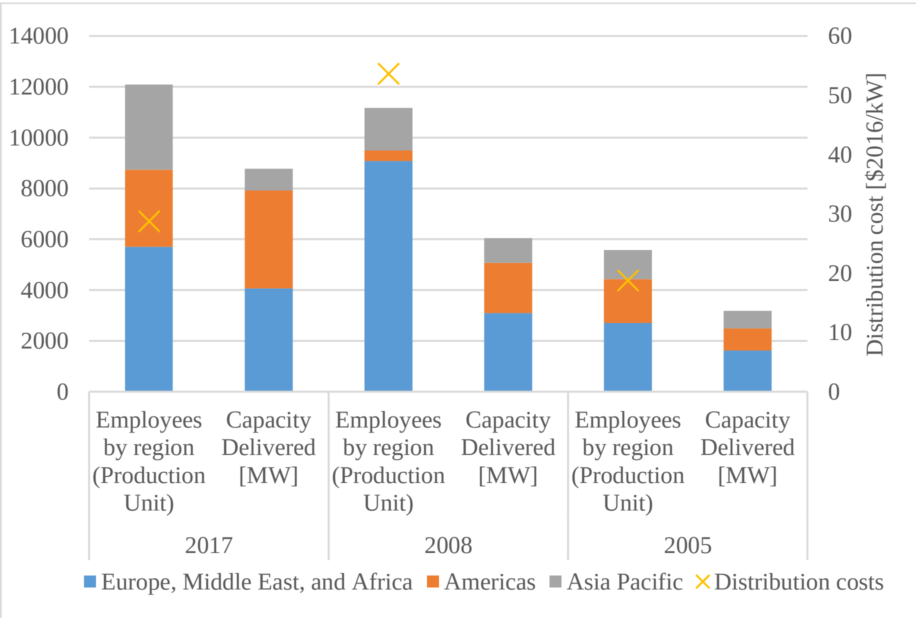


Figure 3-5. Distribution costs by Vestas compared with employees' number (production metrics) and capacity delivered (market metrics) by regions.

3.5.6 R&D, financial and legal costs

It is complicated to disaggregate each of these cost components, the best data available are from NREL reports [168] which provides the annual percentage impact of legal and construction financial costs on wind turbine prices. R&D costs are from Vestas financial reports [170]which provides the costs of R&D department. The level of details of these data do not allow to separate any labour and depreciation capital costs intrinsically accounted in the R&D department thus this value may be considering some double counting.

Legal and financial cost components are considered to be driven by learning by-deployment because are connected with industry management achievements and size growing [25], while R&D costs by learning by-researching

3.5.7 Company profit

Profit represents the margin earned from the company between the production costs and the selling price, a company must have a margin on profit to continue to operate the business. In the case of wind turbine industry profit margin varies with external market effects as global demand raising, changing of costs of raw supply, global financial crisis. Figure 3-6 shows operating profit margins in the last 3 years (2016-2018) are starting to compress in most of turbine manufactures due to decrease of demand of wind projects or alignment reached with government policies. Moreover, the increase of competitors in the sector requires competitive selling prices relative to turbine performance [192]. Production costs need to decrease to maintain the same margin on profit and selling to a lower price without need to decrease reliability and quality. Profit presents a big volatility in values between companies, this parameter results to volatile during the time period to be used with robustness in this analysis, and it also presents negative values in certain years (Figure 3-6). Vestas profit increased until 2008 thanks to demand rise, after it, it starts to fall reaching a down and negative peak in 2012 during the global financial crisis and Vestas financial crisis, and then it starts to rise again.

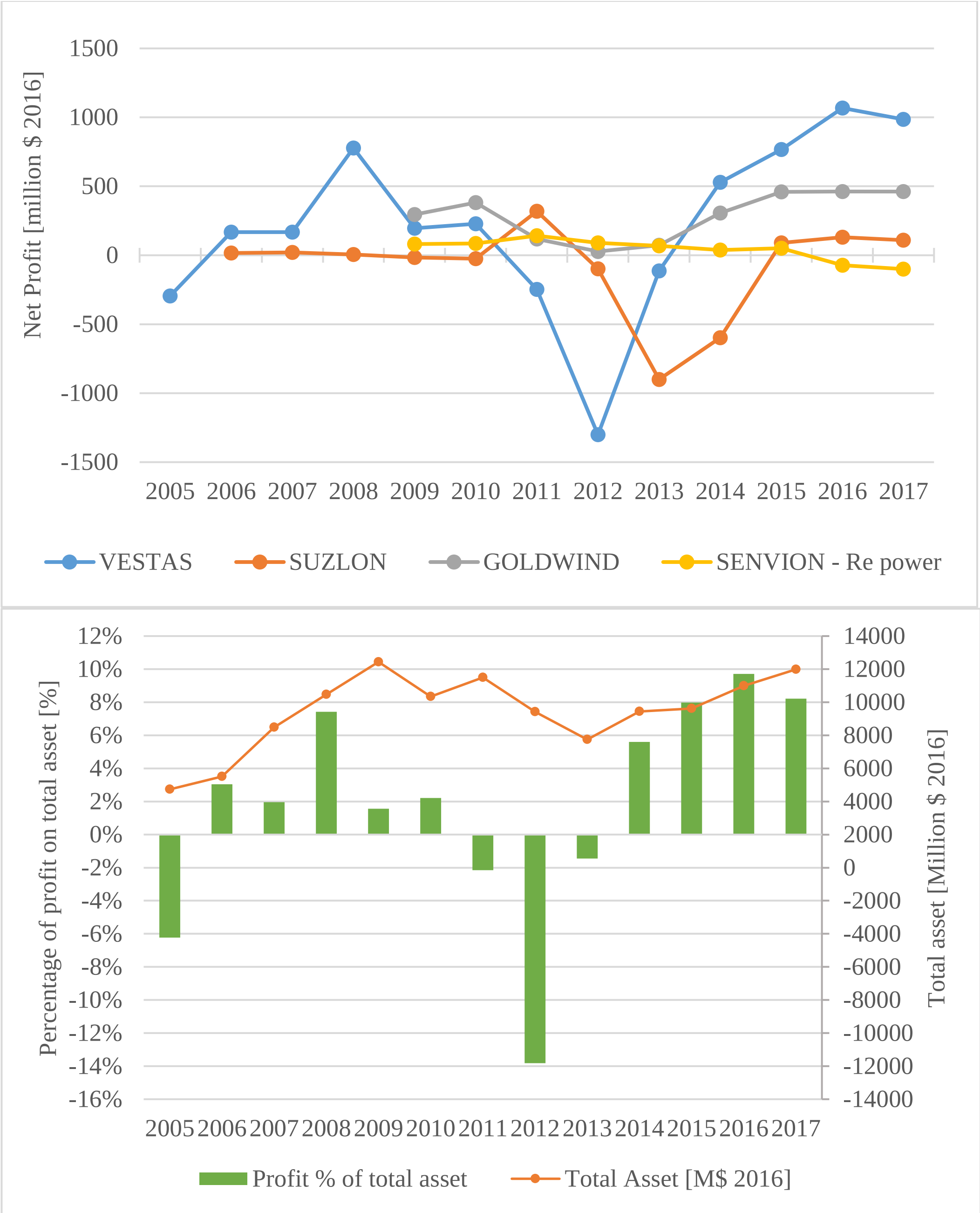


Figure 3-6. Net profit comparison between manufactures. (top figure) Net profit values. (bottom figure) percentage of profit on total asset (left vertical axis), total asset (right vertical axis).

To evaluate the effect of profit variation on selling price we assumed a return on investment of 8% on the total asset, which takes into account both equity and liabilities, this is a qualitative assumption being clear that profit is a component of turbine price, but its volatility means it is not a useful metric to account for the necessary margin over direct costs required to provide an adequate return on capital invested (equity and debt).

3.5.8 Supplier & other costs

With the best current data available all the other costs are considered residual, for example, as discussed in [155], warranty provisions are related to the quality of the turbine sold, an increase or decrease in number of warranty claims today will eventually influence the size of the warranty provisions set aside for future claims. Risk and guarantee can have less impact for mature technologies but having a higher impact in case of emerging technologies [193]. Moreover, reaching the industry growth stage, manufacturers focus on assembly, testing, and design of turbines, and they rely increasingly on suppliers for components production and other sub-services [94, 155, 186]. Suppliers costs can have a major impact during commercialization, they are driven by local supply-chain industry formation, with the increase of competitors their bargaining power decrease. In the last two decades, the industry formation in US contributed to decrease the costs of wind turbine technologies, and since 2005 component manufactures passed from 40 to 450 in 2011. It is expected that suppliers costs decrease with the increase of competition in the market, knowledge spillover and strategic agreements between manufactures and suppliers [194].

3.5.9 Cost components and drivers link assumptions

According to the drivers' categories in Figure 3-3 we grouped the cost components as in Table 3-4 based on the following assumptions.

Improvements in the material usage are largely achieved thanks to learning by-researching as the reduction of blade weight for big size turbines, however, maybe some cross-over with improved manufacturing techniques to build wind turbine components [195-197]. Cost components associated to energy consumptions, and employees' productivity are considered the result of learning by-deployment thanks to knowledge gained in the manufacture with learning by-doing [198].

The material cost of components driven by market prices as labour salary, material and energy prices are considered driven by supply-chain dynamics, many of which are outside the control of the industry, but can be favorably influenced by growth in the scale of the industry itself resulting in more competitive supply chains for specific materials relevant to wind turbines, however, this is not captured directly in this analysis. Salary costs in real-terms have tended to increase with time thanks to better conditions achieved globally for workers, but this cost component varies widely in different countries in terms of absolute levels and percentage change over time, but the benefits of investing in a less developed country with lower labour cost must be balance with the risk of investment associated, thus legal and financial costs in this study [199]. Material prices are influenced by the international benchmark price, that is influenced by geo-political trends and supply and demand balance, for example copper demand has increased as deployment has grown in China and India recently, the risks of supply availability can generate volatile prices that also increase costs [200]. Steel plays a key role not only as one of the main material by weight needs in turbines (excluding foundations) [201], it also applied in many of the production and transmission equipment, as cables, pipeline and generators [200]. Where the price of materials could have a significant impact on the future costs of technologies, an increase in material prices and/or volatility can encourage R&D to reduce materials needs or find cheaper substitutes [197].

Capital depreciation cost is considered driven by learning by-doing, profit by market dynamics related to an increase of competitors as discussed in section 4.7, although in the framework presented here, this only varies based on the total assets employed, as the margin, as already noted is assumed fixed at 8%.[5] Turbine delivery costs are a consequence of progress of an industry in a market, thus driven by learning by doing and market dynamics. These costs can also be driven by more efficient service technologies, in this case they are related also to learning by-researching. Legal and financial costs are associated to company improvements thus to learning by-doing, while R&D costs are associated to learning by-researching. It is possible that little improvement in these costs will be unlocked over time, although some scale effects may be present. The cost component supplier & others covers a range of cost categories that can experience cost reductions form a variety of drivers. For instance, the management of supplier costs which is considered a consequence of variation of competitors in the production market which could reduce suppliers' profit margin at the same time, improved collaboration between the suppliers and the heading company brings to cost reduction, thus industry spillover in learning by-deployment. Furthermore, variation in turbine demand can contribute to reduce the purchase-power of a supplier, which is a demand market driver. Thus, the contribution of each driver is considered to assume a share as in Table 3-4. This

[5] Caution is therefore required in analyzing different periods of wind turbine price evolution, as there is sufficient evidence to suggest turbine availability constraints were an important driver of at least part of the price increase experienced to 2008/09 depending on markets.

breakdown is based on current best assumption since arriving at a more robust breakdown would require data that is not available.

Table 3-4. Drivers assumptions for each cost components

Cost components	**Techno-economic variables**	**Drivers**	**Contribution to cost component (%)**
Material cost	Materials amount	Learning by-researching	100%
	Materials price	Supply market dynamics	100%
Energy costs	Energy/electricity price	Supply market dynamics	100%
	Energy/electricity consumption	Learning by-deployment	100%
Labour cost	Salary	Supply market dynamics	100%
	Employees productivity	Learning by-deployment	100%
Capital depreciation		Learning by-deployment	100%
Delivery costs (distribution + installation costs)		Learning by-deployment	50%
		Learning by-researching	30%
		Market dynamics	20%
Financial and legal costs		Learning by-deployment	100%
R&D costs		Learning by-researching	100%
Suppliers & others costs		Learning by-deployment	50%
		Supply market dynamics	25%
		Market dynamics	25%
Head company profit		Market dynamics	100%

3.6 Results and discussion

In this section the results related to each cost components impact and techno-economic variables is evaluated. We then discuss the effect of the four drivers on cost reduction.

3.6.1 Wind turbine price components

Figure 3-7 shows the changes in wind turbine price due to each cost component between 2005 and 2017. The turbine prices are those of Vestas, but these correlate quite closely to other wind turbine price benchmarks [202] representing a robust indication of wind turbine price trends globally outside of China[6]. Wind turbine prices increased until 2008, rising to an average of around 1700 $/kW in that year[7]. Since then, wind turbine prices decreased, with an annual decline of 10% on average, however, there was an uptick in 2011 where an increase in turbine prices was observed. In 2017 average selling price were around 925 $/kW. During 2005-2008 increase in wind turbine prices is associated with the shortage of supplies caused by rapid deployment of wind industry, as well as increases in commodity prices and the need to adjust production to the increased demand for turbines. The increase in prices in 2011 was associated with Vestas business restructuration to overcome internal financial problems. Due to the difference in overall costs trends between 2005-2008 (hereafter referred to as the "first period") where costs increased and between 2008-2017 (hereafter referred to as the "second period") where costs decreased, we present the results for these two time periods, in addition to the overall 2005-2017 trends.

[6] China is a special case, given that wind turbine prices are often quoted excluding installation costs and their lower commodity prices mean they have prices that track systematically at lower levels to other markets.
[7] The metric unit used to express all costs parameters is $/kW inflated to 2016.

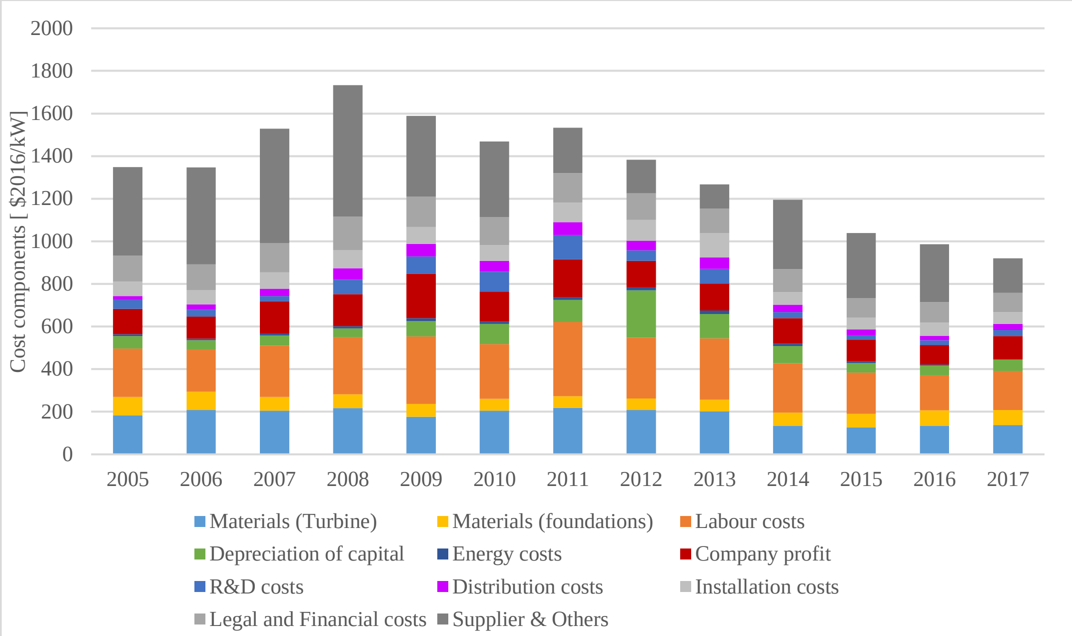


Figure 3-7. Wind turbine and cost components variation in the period of time of the analysis (2005- 2017). The cost components in grey are the one related to less robust assumptions from NREL reports [168]..

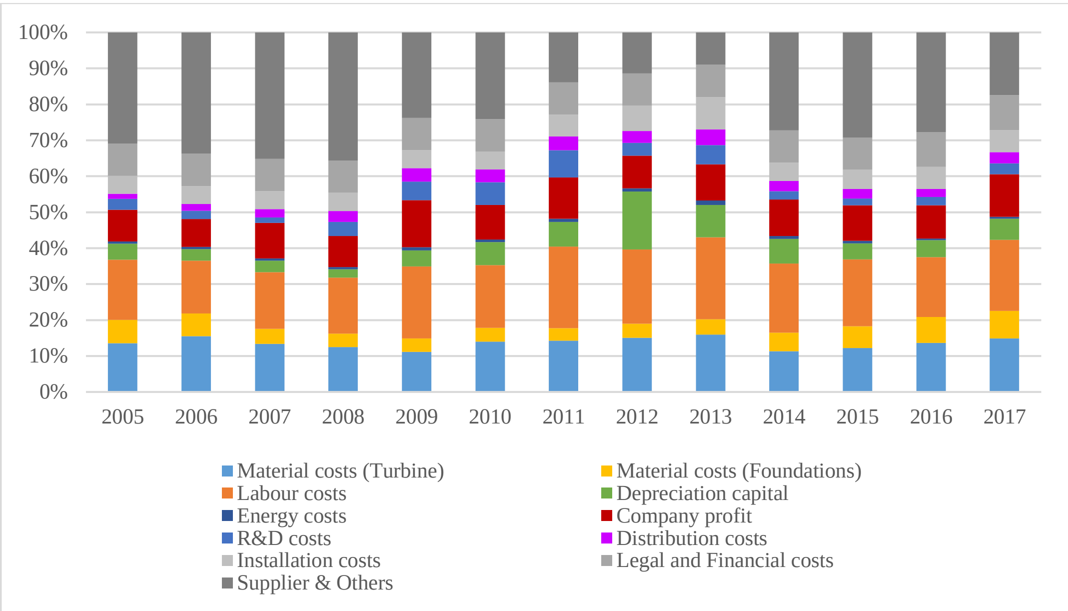


Figure 3-8. Annual percentage impact of each cost component on wind turbine price. The cost components in grey are the one related to less robust assumptions from NREL reports [168].

Table 3-5. Cost for each component in the years 2005 – 2008 – 2017, and contribution to cost reduction in the time periods

[$2016/KW]	Annual Values			Costs changes between two years		
	2005	2008	2017	2005-2008	2008-2017	2005-2017
Materials (Turbine)	182	217	138	34	-79	-45
Materials (Foundations)	87	64	71	-23	7	-17
Labour costs	226	270	183	44	-87	-43
Total Energy costs	8	9	5	1	-4	-3
Depreciation capital	59	40	54	-19	14	-5
Distribution costs	19	67	29	49	-39	10
Installation costs	67	87	56	19	-30	-11
Legal and Financial costs	121	156	90	35	-66	-32
R&D costs	42	67	28	26	-39	-13
Suppliers & Others	416	618	162	202	-456	-254
Company profit	119	150	109	31	-41	-10
Total	1348	1734	925	386	-809	-423
% of cost changes explained by non-residual cost component				49%	44%	40%
% of annual wind turbine cost explained by non-residual cost component	69%	65%	82%			

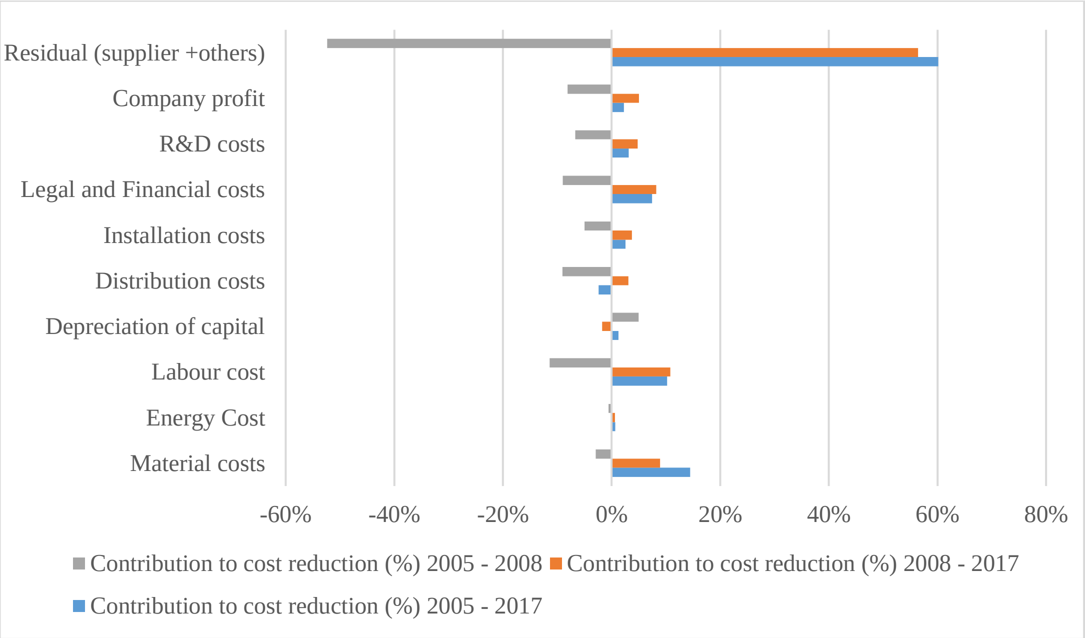


Figure 3-9. Contribution of cost components to cost changes between the time periods: 2005-2008 (cost increase), 2008-2017 (cost decrease), 2005-2017 (overall)

3.6.1.1 *Material cost*

Wind turbine material costs have ranged between 15-23% of total wind turbine price (Figure 3-8), and they contribute to 14% cost reduction in the whole period 2005-2017 (Figure 3-9). Overall, between 2005 and 2017, they declined by 62 $/kW, with only 17 $/kW due to changes for the foundation. They add 11 $/kW to cost increase in the first period and decrease of 72 $/kW in the second period, although interestingly the turbine materials costs increased in the first period and declined in the second, while this is reversed for the foundations.

During the whole period materials efficiency improvement dominated the total reduction in materials cost with a reduction of 56 $/kW, while cost reductions for the underlying price of commodities was just 6 $/kW. During the first period, material market prices reveals an increase of market price for copper, aluminum, iron and steel, while improvements in materials' utilization, particularly regarding steel and concrete, minimized the impact on turbine price increase (Table 3-6, Figure 3-10). During the second period, 2008-2017, material market prices decreased but the switch to bigger turbines (bigger blades size or nameplates >3 MW), preferred in sites with lower wind speed, required high share of structural materials, such as steel and concrete, which explains the increase in cost contribution of these material quantity for the second period (Table 3-6). At this stage of development of wind turbine technology, experienced companies have a wide turbine portfolio which gives the possibility to adopt the turbine choice to site characteristics, performances and material market prices, with a focus on minimizing the cost of electricity generated, in certain circumstances this will result in larger turbines with higher hub-heights and proportionately larger materials balances for the structural components.

3.6.1.2 *Energy cost*

Energy costs contribution appears to be relatively modest impacting for 1% of the wind turbine prices along the whole time-period. It contributes around 8 $/kW in 2005 to the total turbine prices, increasing in 2008 to 10.5 $/kW and falling to 5 $/kW in 2017. The analysis with techno economic variables show both the reduction in average prices for electricity and thermal energy, while electricity intensity declined, but that of thermal energy increased slightly from 2005 to 2017 (Table 3-6, Figure 3-10).

3.6.1.3 *Labour cost*

Along the whole period, 2005-2017, this cost component is responsible for a significant share of turbine price of between 15-23% and of 10% of cost reduction (Figure 3-8, Figure 3-9). Labour cost fluctuated along the time-period reaching the highest absolutes values between 2008- 2013 before starting to decrease again after that (Figure 7). The analysis with techno-economic variable show that employ's productivity was responsible of 47 $/kW labour cost reduction, while salary changes contributes with an increase of 3 $/kW between 2005 and 2017. Employee average costs increased sharply between 2005 and 2008 but have been brought down to just below 2005 levels (per kW).

3.6.1.4 *Capital depreciation*

The impact of depreciation of capital varies along the time period. Its contribution per kW decreases between 2005 and 2008, but then increased, reaching a peak of 222 $/kW in 2012 (16% of the 2012 wind turbines price), this is an anomaly and is probably related to the restructuring Vestas underwent around this time. In the following years it decreased, and the impact lined with the values of 2005, in 2017 it was responsible of 6% of turbine price with a contribution of 54 $/kW. It is expected an higher value during the period of company restructuring, the reduced impact achieved in 2017 is a sign of a better amortization of machine costs and manufacturing scaling effects [203].

3.6.1.5 *R&D, legal and financial costs and turbine delivery costs*

R&D costs contribute on average between 2-8% of wind turbine price based on the example of Vestas and depending on the year. Between 2005 and 2017 they have fallen in absolute terms in their contribution to wind turbine prices, by 13 $/kW. Investment of an industry in R&D is necessary to evolve and compete in existing and new markets against other technologies and other turbine manufacturers and represent an important cost component that needs to be recovered through the turbine price. R&D costs have higher impact from 2008 and 2011, while by 2017 they had fallen to the equivalent of around 28 $/kW and were around 3% of the total turbine price (Figure 3-7, Figure 3-8, Table 3-5).

The assumptions for the cost components for legal, and installation costs already describe the share on annual wind turbine prices, and their annual share increase during the second period, but in term of absolute values these cost components increase in the first period to fall to the equivalent of 56 $/kW for installation costs and 90 $/kW for legal and financial.

Distribution cost has a modest impact along the whole period, between 1-4% of the turbine costs. The absolute value reached 67 $/kW from 2005 to 2008 but fell by around half to 29 $/kW in 2017 Table 3-5. Distribution costs increased when the production and demand market were not balanced, as happened in 2008, and decreased thereafter.

3.6.1.6 *Company profit*

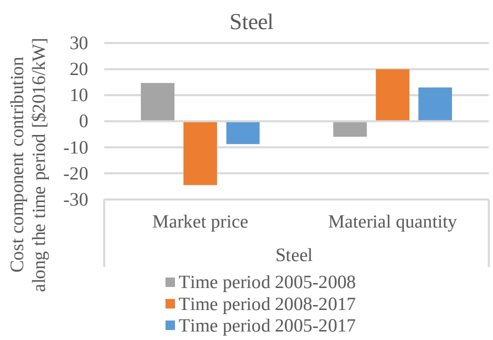
As already noted, the analysis here uses an estimate of a reasonable rate of return on assets in order to provide a proxy for the estimated required long-run rate of profit required. This is due to the volatility in actual profits making historical returns a poor indicator for this component. Profit cost component is responsible of a large share of wind turbine prices, between 8-12% along the whole period. It shows some tightness in absolute values in the last years and bigger values and annual share during the most critical period 2007-2013, this is in line with increase of profit till 2008 but not with its decrease up to 2012 (Figure 3-6). It is probably due to the increase of liabilities and debt on total asset which allowed to guarantee a profit during the financial crisis, thus it is justify its higher impact during that period, without this crisis probably the turbine costs will drop faster between 2008-2012.

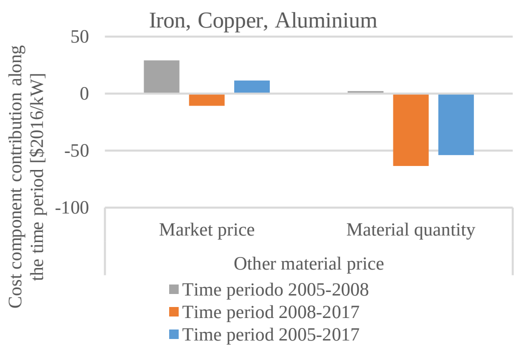
3.6.1.7 *Suppliers & other costs*

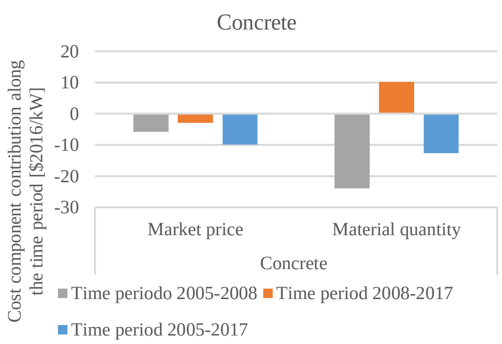
This cost component represents a large part of the annual wind turbine prices with a big standard deviation along the period analyzed (Figure 3-7), it contributes between 9-36% of wind turbine prices in the whole period. In 2005 it contributes for 34% of wind turbine price, while in 2008 it peaks to 36%. After 2008, the contribution is decreasing reaching 17% 2017. In the first period, it increased by around 49% (an increase of 200 $/kW). In the second period, its value reduced by around 74% (Figure 3-9) from $618 (2008) to 162 $/kW (2017), which represent the main cost component contribution to wind turbine price reduction. The exact reasons for this cost component reduction are not clear, but supplier costs category could be driven by supply-chain efficiencies which is expected to improve in a stable market, and manufacture economies of scale. However, without more detailed data to disaggregate this cost component this is only speculation. In any event, even with better cost breakdown data, the supplier costs and management are most probably with the highest share, as explain in section 4.8, and would require a separate analysis to identify drivers of cost reduction.

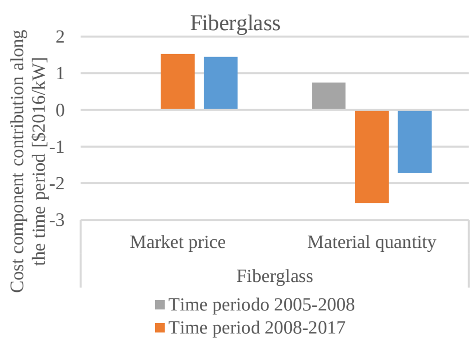
Table 3-6. Contribution in the three-time periods to cost changes for cost components with techno-economic variables disaggregation.

Costs components [$ 2016/kW]	**Techno-economic variables**	**Contribution 2005-2008**	**Contribution 2008-2017**	**Contribution 2005-2017**
Steel price	Market price	14.6	-24.4	-8.7
	Material quantity	-5.9	19.9	13.0
Fiberglass	Market price	0.002	1.5	1.4
	Material quantity	0.7	-2.5	-1.7
Concrete	Market price	-5.8	-3.0	-9.9
	Material quantity	-23.9	10.2	-12.6
Other material price	Market price	29.3	-10.7	11.4
	Material quantity	2.3	-63.5	-54.0
Electricity price	Electricity price	1.0	-2.4	-1.5
	Electricity consumption	-0.1	-1.3	-1.3
Thermal energy price	Energy price	0.7	-1.1	-0.3
	Energy consumption	0.6	-0.4	0.1
Labour costs	Employees productivity	28.0	-76.2	-46.5
	Salary	15.9	-11.0	3.1









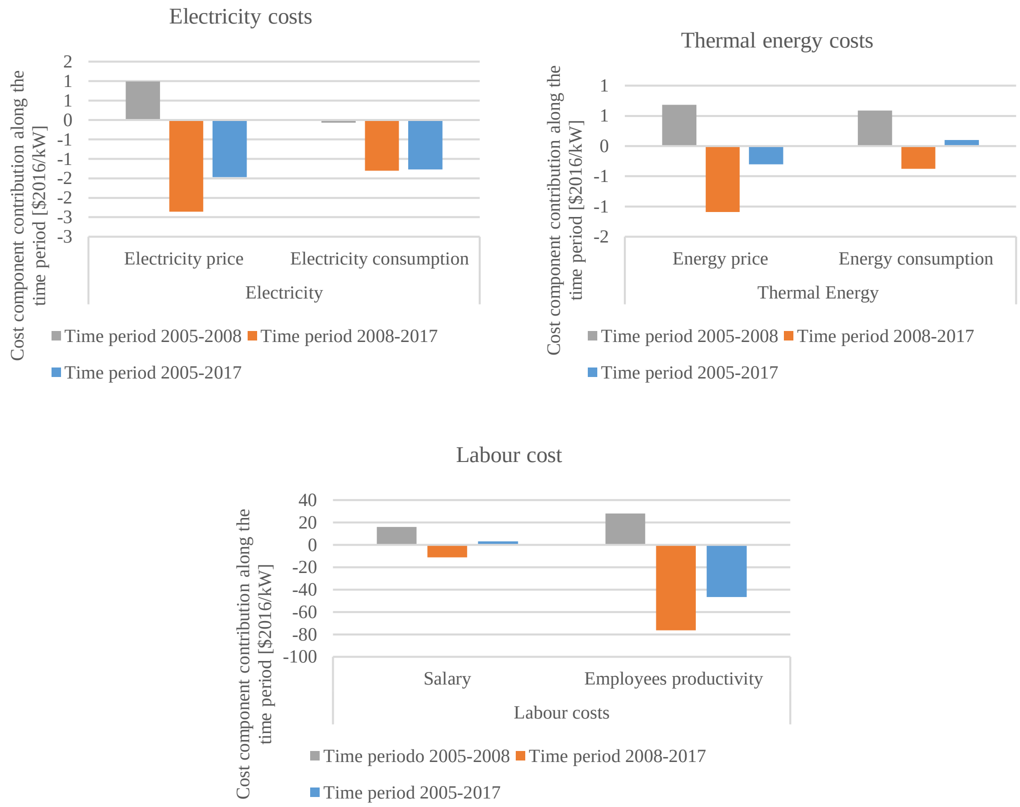


Figure 3-10. Contribution of techno-economic variables and cost components to cost reduction in the three time periods

3.6.2 The contribution of different drivers to overall cost reduction

According to driver categories and association to cost components (Table 3-4, Figure 3-3), the contribution to wind turbine prices due to learning-by-deployment, learning-by-research, supply market dynamics and market dynamics is evaluated (Figure 3-11).

Our estimates show a strong impact of learning by-deployment due to the central role of the industry to promptly adopt in new markets and pulling the pace of costs reduction. This is responsible for 50% of cost reduction, equal to 212 $/kW, between 2005 and 2017 (Figure 3-11). As defined in Table 3-4, it is involved in most of the cost components, it assumed to contribute to 50% of 'suppliers + other costs' because they involve learning inside the company. Moreover, learning by-deployment in this analysis also includes relative effects of knowledge spillovered between actors, and manufacturing scale. This analysis shows the high contribution of employee's productivity techno-economic variable to this driver, reducing the uncertainty related to correlation between cost and driver represented with experience curves (Figure 3-12).

Learning by-researching is the driver category that contributes the least to cost changes (Figure 3-11), it is assumed it does not influence supplier management, while it is driving material cost, delivery cost and industrial R&D. In recent years a lot of the focus has been on improving the performance of wind turbines (Capacity Factor), which does not necessarily translate into reductions in installed costs. Indeed, the use of larger turbines and higher hub-heights tends to increase structural materials needs and costs, although the net effect is a reduction in installed costs over the entire period. The details in Figure 3-12 show that innovation in material quantity is the main contributor to learning by-researching impact between 2005 and 2017.

Of the cost reduction between 2005 and 2017, factors in the supply-chain driver group contributes 16% of the total (Figure 3-11). It includes both material prices and salary changes, the first varies with global commodity markets supply and demand balance, for example copper, aluminum and steel increased until 2011, before starting to decline (see Appendix B for more information). Materials prices are beyond the control of the wind industry, but rising prices will induce some efforts to improve materials efficiency and ultimately might lead to substitution (if possible) with cheaper materials (perhaps after significant R&D efforts). Salary levels and averages will vary based on their location, but also on the balance of employee categories in the wind manufacturing business, which may evolve over time.

Market dynamics driver is linked to all those cost components where the increase of competitors has an impact, as profit, delivery costs, and part of the supplier costs. They contributed 17% of the total cost reduction between 2005 and 2017 (Figure 3-11), as the supply and demand balance in the industry tightened and competition intensified, particularly after 2008. This analysis shows the relevance of this driver once technology reaches stages of full commercialization, indeed, the barriers of deployment and exploitation in new markets influence cost changes.

Table 3-7. Drivers contribution to cost changes along the three periods.

contribution to wind turbine cost changes per each driver [%] // cost components and techno economic variables contribution to cost changes in each driver [$ 2016/kW]			
	2005 - 2008	2008 - 2017	2005- 2017
Learning by- researching	4%	11%	16%
Steel material quantity	-5.9	19.9	13
Fiberglass material quantity	0.7	-2.5	-1.7
Concrete material quantity	-23.9	10.2	-12.6
Other material quantity	2.3	-63.5	-54
R&D costs	25.7	-39	-13.3
Delivery costs (30%)	16.25	-16.54	-0.3
Learning by- deployment	45%	48%	50%
Energy consumptions	0.52	-1.68	-1.17
50% Delivery costs	27	-27.5	-0.50
Financial and legal	35	-66	-32
50% Supplier & Others	101	-228	-127
Capital depreciation	-19	14	-5
Employees productivity	28.00	-76.25	-46.5
Supply Chain dynamics	28%	20%	16%
Material market price	38.09	-36.52	-5.80
Energy market price	1.67	-3.45	-1.77
Salary	15.92	-11.03	3.15
25% Supplier & Others	50.47	-114.09	-63.62
Market dynamics	24%	21%	17%
20% Delivery cost	10.83	-11.03	-0.20
25% Supplier & Others	50.47	-114.09	-63.62
Company Profit	31.20	-40.84	-9.65

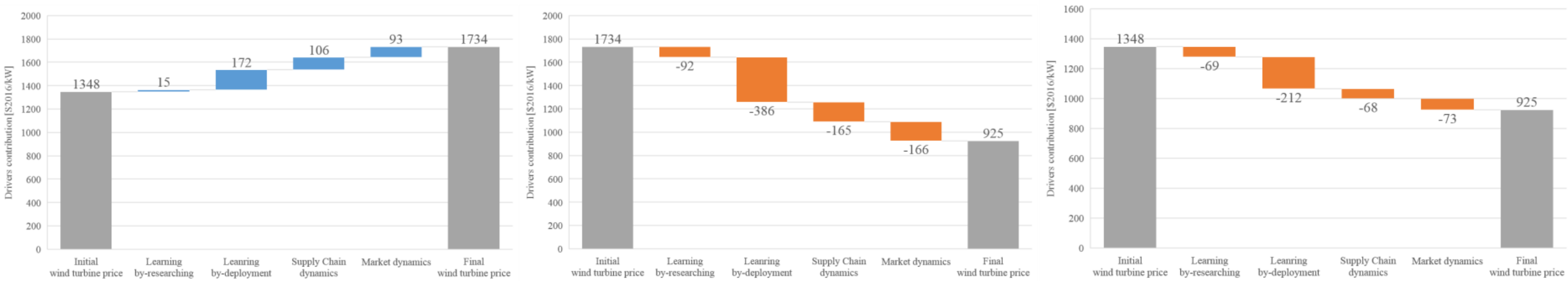


Figure 3-11. Drivers impact along the three time periods. Left side graph: 2005-2008. Central graph: 2008-2017. Right side graph: 2005-2017

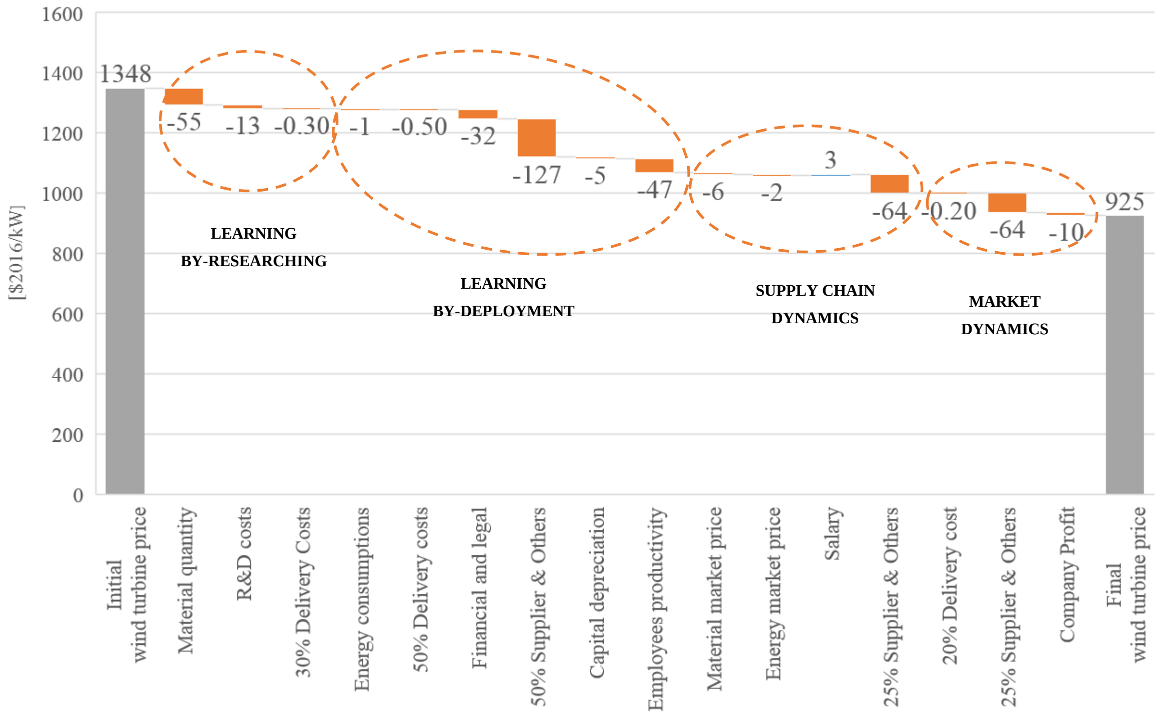


Figure 3-12. Cost changes contribution of drivers divided by the different cost components contribution as in Table 3-4 in the period between 2005 and 2017. Graphs related to the other periods can be found in the Appendix B.

3.7 Conclusion and recommendations

This chapter has contributed to an enlarged understanding of the reasons underlying cost reduction for wind energy. First, the adoption of advanced bottom-up engineering model to disaggregate wind turbine price in its cost components contributes to a better understanding of the effect of each cost component on wind turbine price reduction (Figure 3-9, Figure 3-10, Table 3-6). Second, by developing a cost equation, it is possible to observe the contribution of each techno-economic variable and how they are related to different macro-drivers. Each cost component reduction can be explained by different drivers thereby highlighting the contribution of each driver. In this way a better link between costs reduction and the driver concepts can be found. Such a link should be useful to inform policy-makers on how to prioritise policy-measures to overcome cost reduction barriers in the future.

The findings do explain the contribution to wind turbine cost reduction of different cost components as labour, material, legal and financial, and company profit costs which contributed respectively 10%, 14%, 7% and 2% to the cost reduction between 2005 and 2017.

Moreover, this work also contributed to deepening a layer investigating the contribution of several techno-economic variables influencing cost components variation. The role of technical achievements, in terms of reduced materials consumption has the major impact on material cost component, indeed, during the whole period only 10% of reduction the material cost is due to material prices changes. Moreover, we found employee productivity highly impact labour cost changes and reduced the impact arising from average salaries increasing. While energy costs have a low impact in the whole wind turbine prices, their techno-economic variables contribute equally to this cost component variation. Analysing the results for two periods also reveals the opposite behaviour of some techno-economic variable, for example the variation in quantity of steel and concrete contributes to decrease wind turbine prices in the first period and to increase in the second period. This reveals the impact of large-scale turbine, which improves turbine efficiency to capture energy (capacity factor) although this is not always reflects in a reduction in costs.

In the end, the chapter provides discussion on drivers explaining cost reduction along the two periods. Considering the two periods 2005-2008 and 2008-2017, the drivers impact includes learning by-doing varying from 45% to 50%, supply-chain dynamics varying from 28% and 17%, market dynamics varying from 24% to 16%, and learning by-researching varying from 4% to 11%. This show the success of business models adopted in manufactures (in this case Vestas) and market stimulation strategies adopted to face the market bottleneck. Our findings suggest learning by-researching plays a marginal role comparing earlier stages of development, even if it is increasing again in the latest years, it reached 16% of the impact as supply-chain and market dynamics drivers, it is mainly due to the improvements in material and technology scale. Learning by-deployment is the most impactful driver, secondly supply-chain and thirdly, market dynamics. Still on these two drivers the residual cost component is the main responsible of these share which suggest that the formation of a local and stable supplier chain has an high impact during full commercialization, as well as the stability in new markets regarding risk of investment and regulation. In the case of supply-chain driver, some techno-economic variables as material market prices and salary show the role of this driver with higher levels of detail. In the case of market dynamics driver it is interesting to explore the role of delivery costs on this driver in term of alignment between production local and imported.

This model contributes to a greater understand behind trends of cost reduction of wind technologies revealing the contribution to cost reduction of many important cost components and linking them with drivers. However, the limitations identified leave potential for future research as to improve the understanding of costs components represented in the grey area in Figure 3-7. For example, in this chapter the role of suppliers & other cost category results primary in cost reduction even if it does not represent the main cost component in each year of the analysis. This behaviour highlights two limitations that need further investigation, first, even if the best data have been used some cost components may be underestimated. For example, this study does not take into account the impact of material wasted during the production process, which instead was included in other previous BUCM, as in [25]. The account of this techno-economic variable would increase the impact of material costs and reduce the impact of supplier & other cost component. The second limitation is in the power of the methodology, this implies the existence of a residual cost component which considers all the cost components not disaggregated in the previous categories, and in this case study this is the main component responsible of cost reduction. Thus, a better understanding of this cost component would enrich the results of the analysis. With these improvements in the model, a better drivers decomposition and techno-economics variables analysis would be possible. For example, in this work economies of scale have been aggregated to learning by-deployment and learning by-researching because the data available do not allow more detailed disaggregation, and due to data availability market dynamics are not associated to any quantifiable techno-economic variable. Possibly an analysis at country level may help to improve the model reducing these limitations thanks to better local data available.

Although the analysis in this work is specific to wind, we propose that similar decomposition could be applied to other renewable technologies which prospect similar models of innovation (see [204]). Hence, this analysis could be applied to similar emergent renewable energy technologies, such as wave energy, which presents similar characteristics, as for example a complex design, and similar industry formation pathway or market opportunities and environmental challenges.

Chapter 4

Can wave energy become competitive?

4.1 Abstract

Wave energy presents a potential resource of 29,500 TWh per annum globally but currently only 8 MW have been installed. Despite an increased focus on harnessing this significant resource, engineering and non-technical challenges remain outstanding. A key question is whether wave energy will follow a similar innovation path to commercial viability as other renewable energy technologies. This work addresses this question by presenting a new approach for analysing the innovation needs for an emerging energy technology. Firstly, a techno-economic optimization model is used to provide insights to the scale of cost reductions and energy system characteristics needed to facilitate wave energy deployment by 2050 in one country, Ireland. Secondly, the technology innovation stages behind a historically successful energy technology in a similarly small country, namely onshore wind in Denmark, are identified. Finally, the insights from both approaches are synthesised to provide a wave energy technology innovation needs assessment for Ireland.

4.2 Introduction

Energy technological innovation has contributed to recent decarbonisation of the global energy system, and was a contributory factor behind the adoption of the Paris Agreement [205]. Deployment of marine renewable energy (MRE), tidal and wave, could contribute 4 MtCO_2 annual carbon emission reduction by 2040 and provide significant benefits in an energy system, but still there is a substantial risk of investment for first-movers [206-208]. Globally, wave energy potential has been estimated equal to 29,500 TWh/yr [209]. At present, only 8 MW have been installed [207] with a further 6.8 MW planned in the upcoming years [210]. Cost is a major factor in the slow development so far of wave energy [211-213]. Wave energy innovation is taking place in both large countries (e.g., France, UK, USA) and small countries (e.g., Ireland, New Zealand, and Portugal), despite the latter group usually playing a follower role in the development of new energy technologies [130, 214]. Ireland has an enormous wave energy resource, one of the highest in Europe (50-80 kW/m annual average off its west coast) [215], which increases the possible value of establishing a domestic market and associated national industry [216].

The current phase of development of wave energy is showing challenges, and many technical barriers must be overcome to reduce the investment risk and make it competitive with other mature technologies [217-219]. A key question is whether wave energy development can follow the same innovation path as mature renewable energy technologies to overcome economic viability challenges. Previous analysis on onshore wind and solar PV suggest that successful policy must support all life-stages of the technology development and all the stakeholders involved [220, 221]. While researchers have used long-term energy modelling to develop insights on future technology roadmap by varying assumption on costs and energy system conditions [18], these have often been at a remove from historical innovation analyses that explore the systemic factors driving energy technology innovation [36]. To-date, most modelling studies have used simplified assumptions about energy technology innovation [18, 59]; at the same time, innovation studies have only recently begun to use quantitative metrics [36]. In this chapter the innovation needs for wave energy in a national energy system, Ireland, are investigated from the two methodological perspectives: firstly, by using a long-term techno-economic optimization model of the Irish energy system (Irish TIMES) to develop a range of potential pathways for wave energy deployment in Ireland in 2050 under different assumptions about technology cost reductions and energy system characteristics; secondly, by exploring the innovation stage of development and the role of different stakeholders in driving technology innovation to achieve cost reductions. Due to a lack of wave energy historical records, technology innovation behind a successful renewable energy technology (onshore wind) in a small country (Denmark) is used as comparative case. The insights from the combined methodology applied here therefore allows us to narrow the knowledge gap on innovation needs required for an important emerging renewable energy technology to become competitive.

4.3 Method

4.3.1 Integrated Energy System Modelling

The study uses the Irish TIMES energy system model to quantify the necessary cost reductions to facilitate wave energy deployment in Ireland by 2050. Irish TIMES is a technology-rich bottom-up optimization model that describes all the interactions and pathways between energy supply and energy demand, while accounting for techno-economic system attributes, the required energy service demands and environmental constraints [222-224]. Mathematical equations are used to describe the relationships between the technologies and commodities exchanged (flow of energy, materials or environmental), and linear programming and an objective function that minimizes total system cost are used. The outputs include total discounted system cost, technology investments, installed capacity, fuel type, emission trajectories, and the marginal price of energy commodities [225]. The model enables observation of the deployment of technologies and to understand the impact of system choice in this deployment.

Baseline climate constraints imposed are an 80% reduction in CO_2 emissions by 2050 relative to 1990 (*JRC-CO_2-80*) [226] with combinations of cost and policy scenarios also developed. Initial cost projections for MRE technologies (tidal, wave) are expert-based projections for the EU and come from the ETRI-2014-JRC report [227]. A learning curve is applied exogenously in the model with cost assumptions from ETRI-2014-JRC report varying in a range from 10800 $€_{2016}$/kW to 1922 $€_{2016}$/kW for tidal capital costs, and from 9080 $€_{2016}$/kW to 2300 $€_{2016}$/kW for wave capital costs, in a time period of 35 years (2015-2050). Additional cost scenarios include further reductions of 20%, 30%, 40% and 50% of the 2050 capital costs of MRE (*JRC-20%, JRC-30%, JRC-40%,* and *JRC-50%)*. The costs for the other years are fixed the same as ETRI-2014-JRC report assumptions until

2020 and reduced by the same amount of 2050 in 2030 and 2040. Fixed operating costs have been reduced following the same method used for capital costs: fixed operating cost assumptions from ETRI-2014-JRC report vary in a range from 364 $€_{2016}$/kW to 93 $€_{2016}$/kW for tidal capital costs, and from 308 $€_{2016}$/kW to 113 $€_{2016}$/kW for wave capital costs, in a time period of 35 years (2015-2050). Moreover, other scenarios which are considered interesting from the point of view of observing marine energy deployment are incorporated. One scenario includes limitations in bioenergy availability, in particular a scenario that only allows domestic bioenergy resources, i.e. no bioenergy imports (*CO_2-80-DB*). Another scenario allows increased grid integration of non-synchronous electricity generation, increasing the current annual average limit (50%) to a higher limit (70%) (*$C0_2$-80-ASY70*), and a scenario that combines these two constraints (*$C0_2$-80-DB-ASY70*). All these scenarios investigate the circumstances in which MRE forms part of a least cost technology pathway in Ireland. The same resource potentials are used for all the scenarios, except in scenarios DB (Domestic Bioenergy) where different bioenergy availabilities are imposed, in this case imports of bioenergy are forbidden, then the value is given an upper-limit of 0. Domestic and imported bioenergy potential is based on analysis from Ireland's national energy agency [228]. PV, onshore wind and offshore wind are characterised by seasonal, day and night variability in the model. Ireland has an high availability of marine energy the limits used about tidal energy are based on practical and accessible water resource on [229], for wave energy the resource data are based on the analysis conducted by Marine Institute on a Pelamis device (attenuator device type) on accessible water resource [215].

The advantage of TIMES modelling is the ability to identify the necessary future cost reductions for wave energy deployment in Ireland. It highlights the most favourable system conditions under which wave energy deployment is observed. A drawback is that the modelling analysis does not identify the contributing factors behind wave deployment and cost reduction required in the upcoming years to advance the technology innovation process: for these reasons the analysis is complemented with an historical analysis.

4.3.2 Systematic analysis of historic wind energy cost reductions

This work brings together with energy system modelling an historical innovation approach, analysing the contributing factors to energy technology cost reduction. This approach allows an analysis of cost reduction from a holistic point of view, by focusing on the whole innovation process of a technology within the energy system, as the roles

of incumbents stakeholders, rather than on a narrow view point on one specific aspect as for example the role of technology design. Historical case studies have been used to investigate energy system technological change, and energy technology innovation [230, 231], and the value of their insights has been recognised in the literature [232].
Since wave energy is an emerging technology without an innovation history a comparable technology case study is used in the analysis, namely onshore wind energy in Denmark from 1970s to the 2015.

Because the success of a technology innovation is highly dependent on his context [204], the choice of the historical case to apply the technology innovation framework described above is based on the following specifications. First, the technology type, technologies differ according to the grade of complexity as the number of components and product architectures and the capacity of modularity in its production process [204]. We considered wave energy technology a design-intensive product with a low grade of modularity in the production process. Secondly, the case study needs to be based on an area leader in technology RD&D with strong government involvement. Moreover, the region picked has an abundant energy resource but a small and peripheral market of deployment. With these characteristics a similar context comparable with Ireland can be analysed. The use of onshore wind is considered a comparable case study, it is a mature renewable energy technology that followed an incremental development, from small size to large size wind farm and wind turbines and moved to a concentrated production organization in different markets globally. The analysis does not include other components or service reduction costs such as energy storage for wind [97]. The Danish case is an example of a small and peripheral country which was the core of innovation for onshore wind. Moreover, wave energy devices show a complexity of product architecture which situates this energy technology in a design-intense product category as the case for wind turbines [204]. In the end, the choice of onshore wind was also based on considering the current state of art of wave energy (early stage of development), in a near-future (10/15 years ahead from now) it is probable that other technologies should be considered for this historical innovation analysis. For example, offshore wind could give major insights about the innovation needs required to deploy in the markets and any challenge to face to deploy in an ocean environment.

The analysis investigates the contributing factors at different stages of development of technology innovation, from R&D, to demonstration, to early growth, to full commercialization [8, 60, 233, 234]. Technology innovation involves the role of different stakeholders and here they are analysed by focusing on the contribution of macro-groups of stakeholders such as knowledge institutes, industry, market stakeholders, policy makers, and landscape actors (i.e. broader society) [34]. The chosen structural framework is considered the most interesting to provide a picture of successful innovation process and to identify the effects on costs reduction. It is considered that technological innovation does not happen only within a technical and research context, but the technological change is a result of ongoing relationships and actions between the different actors in a national context (research, industry, market, policy, and society) [31]. This qualitative approach to discuss the elements of technology innovation that drive costs reduction in onshore wind technology innovation shows the steps of technology innovation and what is needed to achieve it, also defined as innovation needs. They complement the results obtained with energy system modelling about costs reduction and energy system conditions, and they allow to critically discuss this innovation needs for an Irish wave energy prospective. This means that the innovation needs are then discussed for wave energy in Ireland and it is argued when these needs can be observed in energy modelling, when instead this is not possible we discuss them with the help of the innovation analysis (Table 4-4 and section 4.4.3).

4.4 Results and Discussion

4.4.1 Energy modelling to quantify cost reduction requirements

The outputs of the analysis reveal the following (Figure 4-1, Table 4-1). **First**, tidal and wave energy respond to the same energy demand, thus they are in direct competition in all scenarios: tidal energy is initially installed because it is less expensive, but references suggests that tidal energy availability in Ireland is limited to 2.63 TWh/year [229]. **Second**, MRE deployment by 2050 is not observed in the scenarios with EU-wide based baseline cost assumptions, with one exception. When the baseline MRE cost curve is reduced by 20%, deployment of tidal energy and wave energy is observed only in scenarios with domestic sources of bioenergy (*JRC-20%-CO_2-80-DB*), with 70% annual non-synchronous electricity (*JRC-20%-CO_2-80-ASY70*), and the combined case (*JRC-20%-CO_2-80-DB-ASY70*). In the scenario *CO_2-80* (i.e. without these additional energy system characteristics) an additional 40% MRE cost reduction is required to observe very limited tidal energy deployment (*JRC-40%-CO_2-80*). **Third**, the primary energy mix affects deployment, with the parameter that most highly influences MRE deployment being the availability of bioenergy, i.e. in scenarios without imported bioenergy, more MRE is installed. For example, in the *JRC-CO_2-80* scenario the amount of bioenergy is equal to 42% of total primary energy supply, with 63% of the bioenergy imported, and no MRE is installed; whereas in the full ensemble of *CO_2-80-DB* scenarios increased adoption of natural gas and renewable energy is observed, with a consequent increase of MRE deployment in 2050. **Fourth**, the level of electrification in all scenarios increases, for example electrification in the total final consumption increases from 19% (in 2010) [235] to a low of 25% in *JRC-30%-CO_2-80* and to a high of 50% in *JRC-30%-CO_2-80-DB* (in 2050). Gas generated electricity with Carbon Capture and Sequestration (CCS) provides dispatchable support to the renewable technologies installed. **Fifth**, among renewable electricity technologies, the role of onshore wind remains dominant; a reduced adoption of offshore wind is observed by decreasing the MRE technology costs, only in *JRC CO_2-80 DB-ASY70* offshore wind is deployed as a direct competitor to wave energy. The following conclusions are drawn from the energy systems modelling analysis: First, significant additional technology cost reductions are required (Table 4-1), which means technical and reliability improvements must be achieved. Second, technological improvements alone are insufficient for deployment; infrastructural improvements are also necessary for increased grid flexibility and for sustaining the higher electrification levels in 2050. Third, the role of primary energy supply in the energy system cannot be discounted; as was seen in the results, limited availability of bioenergy increased the deployment of various technologies, including wave, offshore wind and gas CCS.

Table 4-1. Marine energy deployment results for each policy scenario in 2050. Only results for scenarios with deployment achieved with less additional cost reduction are reported.

Scenarios		Capital costs [€2016/KW]	MRE deployment [GWH]	Total electricity produced [GWH]	Percentage of power generated with MRE [% capacity]	MRE installed capacity [GW]
JRC - 20%	DB	1860 (wave) 1520 (tidal)	15206 (wave) 0 (tidal)	74613	20%	4.33
	DB-ASY 70	1860 (wave) 1520 (tidal)	15867 (wave) 1655 (tidal)	65542	24%	5.16

	ASY 70	1860 (wave) 1520 (tidal)	1828 (wave) 1656 (tidal)	38941	8%	1.15
JRC – 40%	CO_2-80	1400 (wave) 1140 (tidal)	0 (wave) 182 (tidal)	39350	0.4%	0.062

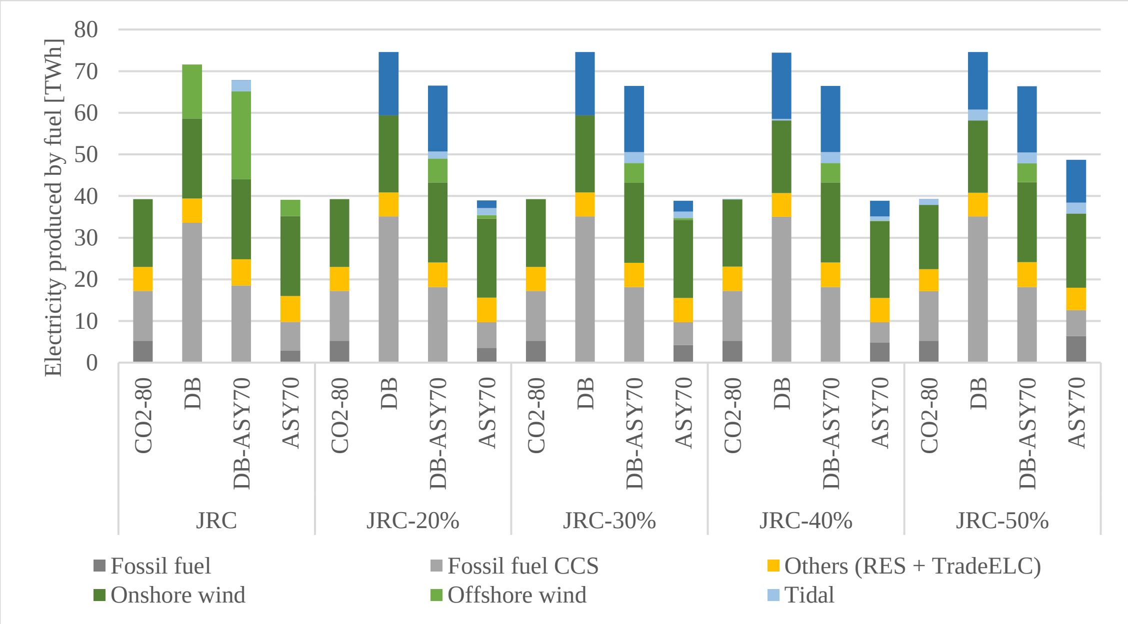


Figure 4-1. Electricity produced in 2050 by fuel for each scenario analysed under different cost and policy assumptions (from baseline JRC assumptions to 50% additional reduction of marine energy costs)

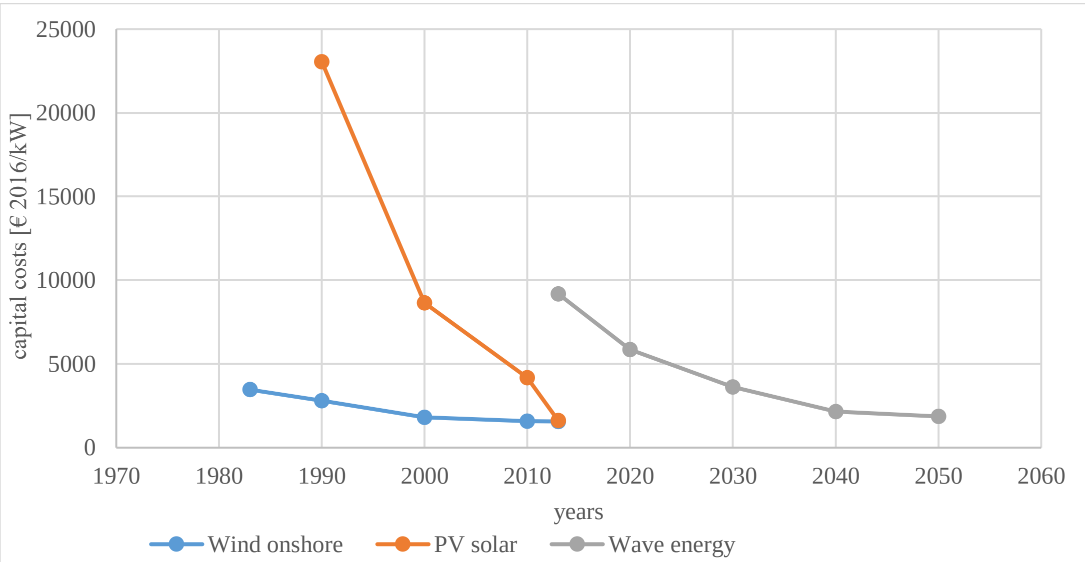


Figure 4-2. CAPEX reduction cost in time. Sources: Solar Crystalline Si PV (1990-2013) *[2, 236]*, Onshore Wind (1983-2013) *[2, 237]*, Wave energy : 20% additional reduction cost assumption from base assumption in *[227]*

4.4.2 Systematic analysis of historic wind energy cost reductions

Having identified the necessary future cost reductions for wave energy viability in Ireland, a historical precedent by comparing scenario-based capital cost profiles for wave energy with historical capital cost profiles for solar PV and onshore wind is identified (Figure 4-2). Table 4-2 summarises the findings discussed in the section below about the historic wind cost reduction in Denmark, highlighting the stakeholders along the stage of development of wind energy technology, their role in pushing forward the innovation process and impact on reducing costs.

Table 4-2. Analysis of historic cost reductions for wind energy in Denmark. Each pane presents results for different development stages, i.e. innovation stage (-1970s), demonstration stage (1980s), early growth stage (1990s), full commercialization (from 2000)

Actors groups	Contributing factors in the system	Their role of in wind energy innovation process	Impact on cost reduction (learning effects)
RESEARCH INSTITUTES	Risø research centre (DK), IEA R&D wind TCP, EWEA (international)	Testing Danish Design Turbine as main design. To exchange knowledge to overcome technical barriers	Improving technology and reducing technical issues. Moving towards one standard design
INDUSTRY	Manufactures: Vestas (DK), Danregn/Bonus-Energy (DK)	Improving technology and manufacturing process. Supporting installation of first turbines.	Benefits in technology improvements thanks to spillovers with research institutes
MARKET STAKEHOLDERS	1. Local wind farm communities 2. Californian Market (exploring)	1. Direct and well connected market for national manufactures 2. Bigger business opportunity in a policy generous market.	1-2. Testing the current technology in protected and less competitive markets. 1. Direct relations between manufactures and customers (learning by-using)
POLICY and REGULATION	1.First Energy Plan (1976), Danish Energy Authority 2. Subsidies for national small wind turbine installations	1. In-country support of R&D, defining strategic role of Risø test centre 2. Nourish a local initial market (65$ million boosted private investments)	1-2. Reducing costs of licensing and other services by using local institutions. Reduce the risk for private investors.
SOCIETY	1. Association wind Turbine owners (1978) 2. Danish utilities sceptical	1. Facilitate the relations between land-owners and cooperatives with public authorities, utilities and manufactures	1. Reduced halt in the market due to social opposition
RESEARCH INSTITUTES	IEA TCP (international)’ Risø (DK)	Focus on economies of scale, grid connection and environmental impact.	Benefits in technology improvements thanks to spillovers between R&D and industry
INDUSTRY	1. Manufactures: Vestas (DK), Danregn/Bonus-Energy (DK). 2. Grid companies	1. Interaction between different research institutes and national wind developers. 2. Agreements to extend the grid (1986)	1. No-rush industrial policy to scale-up technology with reduced the risks and failures. 2. To guarantee a strong transmission grid.
MARKET STAKEHOLDERS	1. Local wind farm communities 2. Californian Market (deployment)	1. Direct and well-connected market for national manufactures 2. Trial market for Danish technology, established designs superiority.	1. Enhancing learning in manufactures thanks direct connection with users 2. Foster technical and economic feasibility in a protected niche market
POLICY and REGULATION	1. Danish Wind Turbine Guarantee 2. Subsidies for national small wind turbine installations 3. 2nd Energy plans	1. To allow the central role of national research and test centres 2. To bring back national industry to install in-country 3. To define first emission and energy national targets.	1. Local supply chain advantages 2. Reduced deployment halt due to society concerns. It saves wasting of time and resources 3. Promoting market pull-demand push policies with full policy support
SOCIETY	Privates and cooperatives	Direct role of land owner in wind energy system, not only as electricity customer	Their collaboration reduce cost to develop infrastructures in private lands
RESEARCH INSTITUTES	International programmes, universities	Investigation of stand-alone wind farm for isolated areas	Keeping reducing technical issues for remote installations
INDUSTRY	1. Components and supply chain suppliers: Glasfiber A/S Svendborg Brakes A/S 2. New privates enterprise for turbine certification	1. Strong national supply chain for major components of wind turbines, competitive internationally 2. To satisfy the arising of market expansion and request of Danish turbines design abroad	1. Acquiring leading knowledge also in the supply businesses. Reducing service costs. 2. Leading role of Danish institutions allows to pose the required standards and the prices
MARKET STAKEHOLDERS	1. Utilities and industrial players (national market) 2. International market	1. to attract industry to pursuit in-country installation 2. Danish manufactures are leader of installation globally	1. Effect of economies of scale 2. Learning by-doing gained nationally applied in bigger than Denmark markets

POLICY and REGULATION	1. Spatial planning 2. Large-scale turbine program 3. National energy strategies	1. To avoid blockages due to environmental and land issues 2.-3.Policy moves with technology readiness level. Full policy support.	1. Reduced wasting and de-risk investments 2-3 Exploit economies of scale and local supply chain.
SOCIETY	Privates land owner	They provide lands for installations	Their opposition generates delays in installation and extra costs
RESEARCH INSTITUTES	International programmes, universities	Focus on different operating conditions	Improving technology and reducing technical issues
INDUSTRY	1. Manufactures: Vestas (DK), Siemens and other European manufactures (EU). 2. More than 100 national companies, included grid operators, in system services	1. Spreading technology globally through joint ventures and subsidiaries and benchmarking between companies 2. To satisfy the market gap between production and arising of demand for wind turbines	1. It increased opportunities to test the effect of technology economies of scale 2. Shortage of turbine production increased the overall costs until supply chain industry organised again
MARKET STAKEHOLDERS	1. Utilities and industrial players 2. International market	1. Repowering to unlock national market 2. Expanding in bigger market as China	1. New and more efficient wind farms 2. Manufactures economies of scale
POLICY and REGULATION	1. Repowering and spatial plans 2. RES producers Obligation 3. Grid instability commission	1. Policy support in national market 2. Market push to produce RES 3. First moving to face challenges due to market expansion	1. New and more efficient wind farms 2. To oblige to invest in isolated lands 3. Reduce the upcoming rising of costs due to grid line saturation
SOCIETY	Danish wind industry association	Support interests companies in the wind industry	Reduce conflicts between public authorities and companies

The initial impetus to focus on wind energy potential arose during the 1970s oil crisis. In response, the Danish authorities promptly invested in research to overcome technical and economic barriers, first identified as bottlenecks during the 1950s. On the demand-side, subsidies anticipated full market deployment, starting in 1978, which reduced perceived risk in investing in small-scale systems [238, 239]. A research cluster developed along all stages of development, with research conducted by public institutes such as the Risø research centre (the sole authority to perform certification and type-approval until 2000), international programs as IEA R&D Wind TCP[8] and EWEA[9] programs, and private industry. Two experienced manufacturers, Vestas and Danregn/Bonus-Energy, pivoted their core business activities towards the new technology and focused on a restricted number of devices [134, 236], mainly, what subsequently became known as the 3-blade Danish turbine design.

An important factor in wind energy technology cost reduction was the availability of markets for deployment from the early development stages. At a time when the large-scale technology was not economically feasible, smaller wind-turbines were installed (aided by Danish government guaranteed subsidies) which provided an opportunity for local manufacturers to test their devices in a safe market, to benefit from learning by-using feedbacks from local farmers, and to operate almost without competitors. During

[8] IEA R&D wind: International Energy Agency Wind Technology Collaboration Programme
[9] EWEA: European Wind Energy Association

the 1980s, Danish manufactures benefitted from the supportive Californian market policies. This worked as a training ground to test Danish devices and positioned Danish industry in an internationally leading role [134]. After the Californian market collapse in 1987, new supportive in-country installation policies in Denmark enabled national manufacturers to deploy at scale in Denmark. At the same time, the national market shifted to different customers, away from the 1980s initial markets based on private individuals and cooperatives and towards the 1990s market of utilities and industry players, which coincided with a shift to incrementally larger turbines [240]. The initial small wind turbine-based market proved to be a successful trial that stimulated learning by-doing, nourished public acceptance, stimulated the regulation process, and anticipated infrastructure investment into the transmission grid.

Importantly, a policy of not rushing technological scale-up helped technical and economic feasibility. Scale-up potential was first tested in 1988 with a demonstration 2 MW turbine [134], but such turbine sizes were deployed only during the first decade of 2000s (Table 4-3). In addition, public policy support was also characterised by a long-term policy planning approach to renewable energy technologies, i.e. since the 1980s renewable energy targets and GHG emission reduction targets were imposed [41, 134] which provided long-term certainty to sectoral investment.

A characteristic aspect of the growth phase was both the formation of a national supply chain for wind onshore services and the expansion to new countries through joint-ventures and subsidiaries. At this stage, economic reliability had been achieved, electricity market liberalization and improvements in grid capacity increased the wind turbine demand, and further cost reductions depend on the capacity to adapt to markets and production competition [241] [240]. A hugely important factor was the industry capacity to adapt to "growing pains": Danish companies exported most of their products due to the limited national market capacity from the mid-1990s. The halt in the national market (2004-2008) due to both internal policy changes and the saturation of lands available for on-grid applications (spatial plan 1996/1997) [240] [62] did not stop turbine production as companies continued to export their products and partially relocate their business abroad. By 2001, 45% of wind turbines globally were installed by Danish companies, in 2013 they still held a 25% share in the global market [134] [242].

While policy was supportive of technology development at many stages, it was sometimes misaligned with market developments. During the 1980s & 1990s, inconsistent policy support significantly slowed wind energy progress. For example it took seven years (1985-1992) to implement the 1st program to finance the installation of 100 MW of large turbine size, and 6 years (1990–1996) for the 2nd program for additional 100 MW, with the two reasons behind the delay being (1) a rush to satisfy market demand while government was still struggling with the processes of permissions and regulation and (2) land-owners opposition to wind farms installation due to the changing focus of policy incentives from the private owners to national utilities [243]. The presence of stakeholder associations contributed to finding a resolution for these conflicts.

Table 4-3. Wind energy turbine innovation and market deployment. Data based on: technology average size [134, 244], rotor blades and tower height average [2], turbine costs reduction [2, 134], capacity expansion [181]

		Technology size (kW)	Rotor blades length (m)	Tower Height (m)	Capacity Factor	Cost [€ 2016/kW]	Danish Market expansion [GW]	US market expansion [GW]	Global market expansion [GW]
Innovation stage (1970s)		200	12	-	-	-	-	-	-
Demonstration stage (1980s)		170	10	20	20-21%	2400-1900	0.3	1.2	
Early growth stage (1990s)		647	25	40-45	19-23%	1900-1250	0.33-2.4	1.2-2.6	4.8-17.7
Full commercialization	**2000-2008**	2000	40	70-80	21-27%	1300-1700	2.4-3.2	2.6-25.4	17.7-116.5
	From 2008	2529	50-60	80-120	27-33%	1300-900	3.2-5.4	25.4-87.5	116.5-514.8

4.4.3 Synthesising findings to identify wave energy innovation needs

Here, the insights and lessons from the modelling analysis and historic analysis in terms of innovation needs are highlighted and then critically discussed for wave energy in Ireland. In some cases, clear innovation needs are identified based on the historic analysis, without supporting insights from the energy system modelling analysis due to the current model structure and assumptions; in other cases, some of the innovation needs that are relevant can be reinforced and enhanced with additional quantitative insights from the energy systems modelling analysis (for details on the innovation needs to see Table 4-4). Commonalities and more importantly gaps in one area that could be partially addressed by insights from one of the two approaches are identified.

The innovation needs outcomes discussed here should be seen as areas of focus to support the implementation of specific policies for emerging renewable technologies innovation, respecting the characteristic of the whole energy system, as well as resource availability, location, and technology type. The perspective of these innovation needs are is discussed for the case of wave energy in Ireland

The emergence of a standard design was a crucial stage for the development of wind turbine technology, marking the end of the formative phase. Wave energy technology is currently far from standardization due to the diversity of environment settings and types of technological approach (off-shore, breakwater mounted, etc.) (Figure 4-3). The range of designs reflects both the difficulty of operating in a wave environment and the diversity of available wave energy resource. For example, Portugal and Italy have focused their research on overtopping and oscillating water column devices, whereas Ireland has focused on oscillating water columns, both point absorbers and attenuator devices. For these reasons, to expect that one standard design will prevail overall in wave energy, as was the case in onshore wind, may not be realistic. It may be hypothesised that, in the long term, only two or three types of wave energy technologies will exist in the global market, each with its own applications in terms of either wave climate or type of deployment; and for each of them, a standard design will have prevailed. A strategy that addresses the innovation need of wave energy device standardization in Ireland would support the emergence of a local wave energy industry. In the near term, future funding may focus on selected technology devices that align with Irish energy wave resource conditions [245].

A need for access to different markets according to the level of technological readiness is clear from the historic analysis, i.e. progressive growth in potential market size facilitates industry expansion. Wave energy is at a technological readiness stage where an appropriate niche market would be an opportunity to test full-scale devices in a commercially protected environment. Gathering performance feedback would facilitate further technological learning. Some countries already have niche markets in development, like desalination plants in Spain, or remote island applications in China [207]. In Ireland, small enterprises (e.g. Carnegie Clean Energy) and large enterprises (e.g. Equinor and the US Navy) have stated an interest in isolated micro-grids as a substitute for diesel engines, even adopting technologies categorised with technology readiness level (TRL) varying between 6-7 [246] [247]; however at present no niche market exists. In addition to the need for an appropriate niche market, there is a need for access to potentially large markets with associated economies of scale. For wave energy, not only are large countries like Spain, Canada and UK developing the technology but so are small countries like Portugal, Ireland and Sweden. However, while these latter countries have a large wave energy resource, their small market potential is likely to present a challenge. Small country industry can be enhanced by developing a frontrunner technology which becomes internationally competitive. Figure 4-4 shows market deployment for wind energy technology in different countries, highlighting the limited deployment in the Danish market.

Improved economies of scale are important and will be influenced by both market size and technological scale. The present variety of wave energy device designs makes it difficult to track technological scale-up progress. Previous studies suggest that scale-up at the technological unit level won't occur until a standard device design emerges [44], as was the case for onshore wind. Therefore there is a need for technological scale-up for wave energy but the diversification of state-of-the-art designs suggests that wave energy is still in a formative phase, too early to achieve a successful technology economies of scale at this stage. As shown for the UK [248], there was a push for accelerating the technology trajectory of wave power towards commercialization and thus a fast shift to large-scale technologies that are far from being cost-effective at these early stages of development. The wind analogue shows successful economies of scale only once technology achieved commercialization and it looks that wave energy may be like onshore wind case, even if the device standardization may occur differently. Further analyses should be done in the future to confirm these economies of scale trend, maybe comparing the scale trajectory of new wave energy devices with wave industry growth and deployment market size.

Furthermore, a niche-market can help finalise a standard design, which in turn will be a starting point to explore economies of scale opportunities [249]. While a standard design is not a niche market prerequisite, it can help improve design in a way that contributes to the standardisation process. The modelling results underline the importance of a large market (i.e. an increase in electricity demand, non-synchronous electrification) and through quantification of marginal cost of carbon at different technology penetration rates, gives an indication of how policy (via carbon pricing) can contribute to markets that promote long-term decarbonisation.

The supportive role of policy at each stage of development, focusing on meeting the interests of multiple stakeholders (Table 4-2) is important. At its present stage, wave energy needs sustained political support in both national and international RD&D

investments. Strong international support such as the International Energy Agency (IEA) Ocean Energy System agreement that facilitates the coordination of research activities between countries, as well as a number of coordination programs between countries, e.g. OPERA, MARINET-2, and INORE10 continue to be important. There is a need for policy that is consistent (i.e. not stop-go, which worsens the technology investment risk), flexible (i.e. to a variety of as yet unknown developments), responsive (i.e. to new technological developments), and adaptive (i.e. to the pace of change in industry such damaging delays are avoided or minimized). It must balance short-term changes with a long-term vision. The modelling results illustrate this through the competition between certain technologies in a future decarbonised system, e.g. between tidal energy and wave energy, offshore wind and wave energy. There is a need for a balanced energy decarbonisation plan to clarify the role of electrification in the energy system, the type of technologies considered relevant for electricity production, and how wave energy technologies could fit in this mix in 2050.

Wave energy deployment will need integrated and supporting infrastructure, which will include both electricity and broad marine based infrastructure. Our modelling results show the importance of the involvement of electricity system operators in the research activity on energy conversion and transmission. Renewable energy supply technology development is intimately connected with the flexibility of the electricity grid and capacity potential. For wave energy, the associated grid network will require the installation of submarine cables, grid connection and substations which requires direct involvement of the national transmission service. Moreover, additional infrastructure requirements need to support the development of wave, for example large port facilities. In this case, financial funding should be addressed for overcoming technical barriers related to the wave energy infrastructures; for both ship building industries and ports to support wave energy the risk of investment in this sector needs to be mitigated through innovation on transportation and installation [250, 251]. To avoid a slow-down in growth due to system integration barriers, the TSO stakeholder should be an active partner in the research projects to investigate the system integration feasibility needed for each wave energy device. Wave, offshore wind and tidal energy can be understood as peripheral

[10] INORE International Network on Offshore Renewable Energy

energy resources in a national energy system and the development of interconnectors would highly influence the deployment of these resources [252].

In additional to physical infrastructure needs, there are also what it is called knowledge infrastructure needs. These come in the form of local research centres and local industry. Internationally, there are a number of potential marine energy niche markets, such as micro-grid, where industry partners are contributing to the project design and relying on international financial support (i.e. CETO 6 Carnegie-CE). For Ireland, an approach to attract international developers to a niche market could increase knowledge spillovers and help structure a local supply chain [253]. To facilitate this, absorptive capacity within local research and industry actors is necessary. For example, the national test centre Atlantic Marine Energy Test Site (AMETS) could apply lessons learnt from the successful role of Risø research centre in wind energy technology innovation [134]. Physical infrastructure can contribute to the growth of knowledge infrastructure with intermediaries such as a marine industry association helping the bridge the gap between actors in this space.

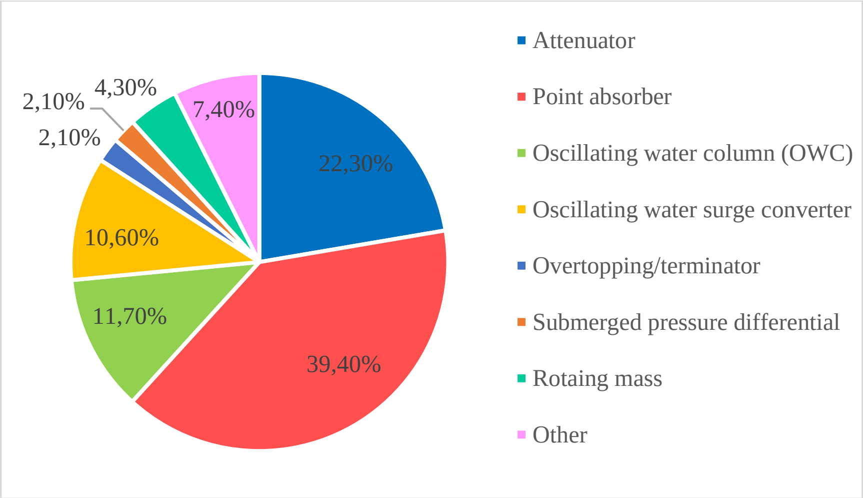


Figure 4-3.Wave energy device designs (global). Based on IRENA project database provided by IRENA

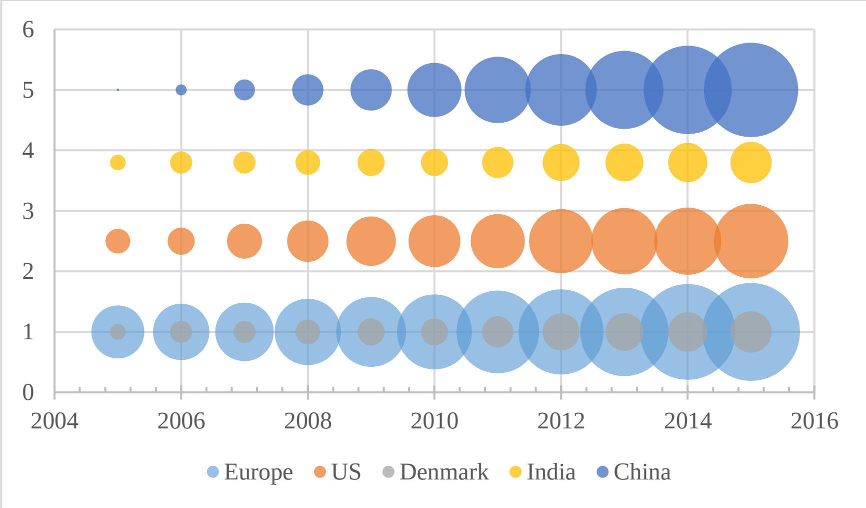


Figure 4-4. Wind onshore market size evolution worldwide compared with Denmark capacity size (absolute values) (ref: [254])

Table 4-4. Wave energy innovation needs - insights and questions that arise from historical and modelling analyses. Numbered with 1. Modelling insights, 2. Historical analysis insights.

Innovation needs	Insights from historical and modelling analyses
A need to implement opportunities for reducing the gap to achieve a **standard design** which would see a shift from product innovation to process innovation	1. The TIMES energy system model employed in this analysis implicitly assumes a standard design in its cost projections and doesn't distinguish between technologies that have a standard design (e.g. wind) and technologies that don't (e.g. wave, CCS). 2. It is an essential stage which supports the emergence of a broader industry especially once pre-existing firms from other sectors pivot into the new sector (e.g. VESTAS originally made agriculture equipment and machinery).
A need to provide flexible access to **different markets** according to technology readiness and industry needs	1. TIMES energy system modelling suggests deployment for wave energy in event of restricted biomass imports and no CCS, but this is highly uncertain and probably doesn't represent a sufficient niche. Moreover, an increase in electricity demand is associated with a higher deployment of wave energy; and it can give an indication of the ballpark for CO_2 price associated with deployment of different technology. The model is limited to Ireland energy system the use of an integrated global model could provide insights on potential other markets. 2. Historical evidence shows the important role as niche and initial market for deployment for small-scale turbines in Danish farms and California market. Likewise, local market moved faster to engage bigger costumers as utilities, and Danish industry became leading industry for developing onshore wind technology, but needed to go beyond to local market expanding after 2000s in new markets as US, China or India developing joint venture partnership
A need for gradual **scale-up at the technological unit-level** which would improve the current economies of scale of wave energy	1. Assumptions about potential for scaling-up are included in the modelling analysis but are aggregated (i.e. technology unit scale and industry scale are merged – assuming technology size increasing) 2. Scale-up at the unit level of the technology is an important stage following the emergence of a standard design. Premature attempts to scale-up can undermine technological development when expectations are not met. Danish approach towards gradually up-scaling according to technological improvements lead them to dominate the market.
A need for **sustained political financial research support and timely preparation of licensing and regulation** to contribute experimentation and learning	1. The modelling results shows that the time durations involved are long: there is no need for wave energy until 2050, some 30 away. This presents challenges from the political aspect which will look for more short-term wins. 2. Denmark invested in the development and demonstration of the technologies locally, with long-term and reliable plans, but technology innovation highly benefits from international innovation programmes, particularly in term of sharing technical achievements. Historical evidence suggests that regulation and permit should be put in place before the expansion phase and a loose regulation inevitably stall deployment and market expansion.

A need for a **balanced energy decarbonisation plan** that includes both long-term and short-term perspectives	1. Irish TIMES modelling provides insights to some of the technology competition, e.g. offshore wind is a direct wave competitor, both in term of grid penetration and potentially of land use, or e.g. onshore wind and CCS showed a complementary role in the power sector in the model results. *2.* The historical evidence suggests that energy policies must take into account the energy potential and possible competitors for each technology at short and long-term (as Danish energy policy). A long-term energy decarbonisation plan is needed to maintain the confidence of many stakeholders, no years' policy gaps or brutal interruptions.
A need for **integrated and supporting marine infrastructure**	1. The TIMES modelling results show that a doubling of system electrification allows a wider technology portfolio. Non-synchronous electricity penetration: Infrastructures' limits can avoid a complete use of intermittent energy technologies. A mix of renewable energy technologies could leverage the problem due to intermittence energy supply. No information on marine sub-components and associated spatial infrastructures innovation are provided by Irish TIMES modelling. 2. Infrastructure and integration system can advance only at the growth stage when few reliable designs are available, because different design require different components, and thus different a supply chain develops
A need for absorptive capacity and **knowledge infrastructure** among local actors to nurture industry formation	1. Energy system models do not provide insights on knowledge infrastructure needs, thus on how the stakeholders group and learn, or funding to institution my help. This is likely to be better discussed in social science fields. 2. The historic case showed the importance of local capacity (e.g. local industry clusters and supply chains) for creating the knowledge infrastructure to help an industry grow. This required a collaborative relationship between research centres, industry, and intermediaries.

4.5 Conclusions

This analysis has described a diversity of innovation needs that exist for wave energy to become economically competitive in a future electricity system in Ireland. These needs have been described in the context of Ireland, but many of them are relevant for other countries that are also investing in wave energy R&D. For wave energy to progress it is important to direct attention and efforts to bottle-necks in technological and commercial development. Articulating innovation needs can help co-ordinate innovation activities. The challenge and importance of aligning innovation needs is also apparent. This analysis has highlighted diverse challenges across the energy system (i.e. competition between intermittent renewables, the role of primary energy and bioenergy imports, the level of electrification), across space (i.e. separate locations of wave energy resource, industrial capacity, electricity infrastructure, knowledge infrastructure), and across time (i.e. short-term needs versus long-term goals, niche market vs large market). Achieving wave energy deployment is not without challenges and aligning wave energy innovation needs across space and time will facilitate improved progress.

This analysis has also highlighted the value from adopting a mixed methods approach. In combining energy systems modelling analysis with historic analysis, it is possible to gain more holistic insights to the innovation needs for wave energy. In addition, through overcoming some of the weaknesses in a single methods approach, the combined approach also helps identify research needs for some of the individual approaches in energy systems modelling. For example, while the historic literature points to the importance of niche markets for the emergence of a standard design and commercialisation of a technology, this is currently beyond the capability of energy system modelling tools. Though the model does provide insights in terms of larger markets, i.e. an increase in electricity demand facilitates wave energy deployment. Further analysis that explores the role for wave energy in a more carbon constrained world in line with Paris Agreement (COP 21) could be undertaken.

Chapter 5 **Conclusions**

The aim of this thesis is to improve the knowledge base surrounding the role of technology innovation in an energy system by understanding and quantifying its impact on technology cost reduction. Moreover, the role of energy technology innovation to accelerate technology cost reduction for emerging energy technologies is also discussed. The thesis addressed the five research questions outlined in section 1.3 which are answered in brief below based on the findings.

RQ 1. How consistent is the energy technology innovation system framework with the drivers' theory of energy technology cost reduction?

Answer: An energy technology innovation system is a complex framework, and the multiple drivers pushing technology cost reduction along the innovation stages of a technology are showed in Chapter 2. This complex structure shows the inconsistency of a single driver method (1FLC) to truly represent the dynamics of technology cost reduction. Indeed, the use of multiple driver methodologies is considered more consistent to represent these dynamics, even if the system is highly complex to investigate and model at the state of art. The use of multiple driver methodologies does not discount uncertainties but instead better represents the real dynamics in the system.

RQ 2. What is the present state-of-art methodologies in quantifying the multiple drivers of energy technology cost reduction?

Answer: There are two main state of art methodologies used, MFLCs and BUCMs. Their applications and insights for onshore wind and solar-PV technologies are discussed in Chapter 2. The MFLCs is the main method applied, but the use of an econometric model to investigate multiple drivers is failing to produce robust and certain results for all the drivers of technology cost reduction. There is a challenge to address the right parameters representing each driver without incurring statistical and methodological limits. BUCMs are a more recent application that is not widely applied, being based on experimental bottom-up engineering assessment it requires a rich dataset, but it may reduce the issue of missing causality between cost and drivers, an intrinsic issue in MFLCs method, but still more analyses are required. Chapter 2 showed the limitations of current methods, in fact, the papers reviewed for the two renewable technologies presented a limited geographical diversification (Table 2-1) and limited variation of drivers' choice, mostly learning by-doing and learning by-researching (Figure 2-3). The main reasons behind these limits rely on the lack of data availability and uncertainties about how to represent more complex driver concepts such as spillovers of learning and market related dynamics.

RQ 3 What insights are gained into the multiple drivers of energy technology cost reduction by applying a state-of-art methodology to a new data set of wind energy technology cost components?

Answer: Chapter 3 adds value to current onshore wind turbine cost reduction analyses, highlighting the current weakness and difficulties within cost analysis. A BUCMs approach is applied and the impacts on cost reduction of four drivers, learning by-deployment, learning by-researching, supply-chain dynamics and market dynamics, between 2005 and 2017 are discussed and quantified. The analysis provides insights about the disaggregation in cost categories along the years, finding that between 40% to 49% of cost changes can be explained by specific cost categories. It also shows the drivers contribution to wind turbine costs changes, the main changes are driven by learning by-deployment in onshore wind technology cost reduction during a full-commercialization stage, but also supply-chain and market dynamics have a relative impact during this stage. Moreover, it shows the positive contribution of learning by-researching in containing material costs of wind turbines once the turbines size scaled during the latest 10 years (Table 3-7).

The evidence of other drivers beside learning by-deployment shows how to base energy policy planning on one single driver may lead to develop inappropriate and simplified conclusions. Regarding the methodology applied, it is confirmed the complexity to evaluate the multiple drivers with the best dataset available, still more analyses are required to reduce the uncertainties about wind turbine costs components and techno-economic variables. By comparing with similar analysis done on solar-PV in the literature, the case of onshore wind turbine presents a more complex technology archetype, most probably an analysis at country level will reduce the uncertainty increasing the amount of data available and allowing also a more detailed drivers disaggregation.

RQ 4. How can the integration of historical analysis improve energy system optimisation modelling of emerging energy technology innovation?

Answer: The combined method developed discussed in Chapter 4 provides a solution to the current limits in including energy technology innovation endogenously in the current ESOMs, topic that is also discussed in Annex I. Alone, Irish TIMES does not allow the identification of multiple drivers of cost reduction and innovation needs required to accelerate technology innovation. An historical innovation analysis reveals the elements that contributed in the past to accelerate cost reduction for a comparable renewable energy technology. This could complement an ESOM to improve the information the role of technology innovation in future energy system. In this way, the insights developed with the current ESOM model can be better contextualised and used to identify the innovation needs required for technology innovation to be achieved. A single analysis could not provide such a deep understanding of innovation needs to accelerate emerging technology deployment. Moreover, an accurate analysis is done to prove the accuracy of the energy technology analogue, by identifying the best fit in term of technology, stage of development, location, and region type.

RQ 5. What are the innovation needs for a particular emerging energy technology (wave energy)?

Chapter 1 Answer: The case study analysis on wave energy in Ireland in Chapter 4 reveals the innovation needs required to accelerate its energy technology innovation. First the costs reductions required for wave energy to be economically competitive in the Irish energy system are shown using scenario analysis with the Irish TIMES energy system model, together with relevant energy system conditions (Figure 4-1). This effectively points to the high level of innovation required to achieve this capex cost reduction. Then an historical innovation approach is used to show how this innovation could be pursued using a technology analogue, onshore wind. The case study shows the dynamics in the system that contributed to technology innovation and cost reduction and, also, how some bottlenecks could prevent innovation in the historical case. Merging the insights from the quantitative modelling scenario analysis and qualitative historical innovation approach enables to a critical discussion of the innovation needs for wave energy in Ireland. This analysis shows the importance of articulating and aligning different innovation needs not only related to technology performances but also related to challenges across the energy system related to policy and regulation readiness and market readiness. For example, the case of wave energy in Ireland shows at the present stage there is a bottleneck in achieving a single standard design as it was for the onshore wind case, which highlights the need of a strong direct policy intervention in term of R&D support, but also that wave energy may develop in more designs according to the market applications and ocean environment. Moreover, specific challenges are related to certain regions with remote resource location as Ireland, thus there is a need of local knowledge and infrastructural capacity to be developed to not halt future deployment. In the end, there are challenges related to time, as balancing policy short-term needs and long-term needs and niche and large markets perspectives.

5.1 Conclusion on methodology

Chapter 2 shows the role of energy technology innovation in an energy system and presents the best methodologies used to investigate the multiple drivers affecting technology cost reduction within an energy technology innovation system.

In Chapter 3 a BUCM is developed for the case study of onshore wind for the first time in the literature. Methodologically, in addition to MFLCs the use of BUCMs enriches the understanding related to the causes of technology cost reduction. To do so, it links costs and drivers through more realistic variables with a higher grade of causality. With BUCMs, drivers can be linked to one or more costs components through a cost equation. The use of this method contributes, with MFLCs, to reduce the unrealistic representation and uncertain results obtained in applying 1FLCs, moving beyond a single factor analysis to investigate cost reduction. In addition, it also reduces the risk of non-robust and vague findings obtained with MFLCs.

Chapter 3 shows that BUCMs also have some methodological limitations, such as the requirement of a robust dataset of variables to perform the analysis, and the infancy method development which requires the investigation of different cost disaggregation and techno-economic variables according to the technology analysed. Nevertheless, it shows the importance to introduce this kind of complex analyses to investigate and quantify technology innovation impact and to show the importance of multiple drivers on different cost components.

Annex I discusses possible solutions to include energy technology innovation in long-term energy system optimization models. At the current state-of-art ESOMs offer limited solutions in the integration of energy technology innovation, the most advanced models apply 1FLCs, but these require high computational effort and do not provide comprehensive findings. The conclusions from the ETSAP workshop highlight the gap in the research field in providing reliable methods for the implementation of technology innovation in ESOMs, the unreliability of 1FLCs integration in ESOMs, the need to expand the concept of innovation also to other variables in the model not only technology cost reduction, and the future actions to undertake within the research community to overcome these issues. Methodologically, the most credited paths to follow to represent energy technology innovation in ESOMs were recommended:

i. To improve scenarios sensitivity analysis of the current models and discuss and analyse technology innovation with an external innovation approach, as it was applied in Chapter 4 of this thesis. This requires the development of interdisciplinary work between energy modellers and researchers focused on technology innovation studies.
ii. In parallel, it is necessary to understand which kind of innovation technologies, elements and actions are more suitable to be implemented in ESOMs sharing the thoughts between the modelling community, innovation practitioners and decision makers. Then, once the best innovation variables are identified, it is necessary to develop new approaches and solutions to represent energy technology innovation with these variables to overcome the simplification of 1FLCs.

The mix of approaches used in Chapter 4, Irish TIMES scenarios analysis and historical innovation analysis, reveals holistic insights related to the innovation needs of wave energy, overcoming the weakness of a single method approach. On one side, it allows the findings from long-term energy system models to be enriched with energy technology innovation required for emerging energy technologies. On the other side, historical innovation analysis alone cannot provide quantitative insights on the role of different variables in the energy system since its main focus is on the past. Thus, the two methods complement each other, and this moving forward projected to the future analysis is improving the understanding of how technology innovation can impact future emerging energy technologies. This analysis allows the possibility to be repeated in a near-term future when more data will be available for the emerging energy technology, these can be used in the energy modelling and according to the new present characteristics a new technology analogue can be used for the historical innovation approach. For example, once market deployment will be achieved an historical innovation analysis on offshore wind can provide interesting insights about the innovation needed for wave energy to adapt to ocean environments.

The methodology recommendation derived from the analysis in Chapter 4 is the necessity to consider the differences between technologies when historical innovation analyses are investigated. Differences between each case study must be considered and argued when the innovation needs are investigated, such as technology types, historical context and energy system context. Benchmarking between two different case studies is useful to learn from the past, but it is important to carefully consider the differences when evaluating policies implications using the historical analysis approach. This concern has been addressed in this thesis critically discussing how the innovation needs identified could adapt to the specific case of wave energy highlighting where they are relevant and primary.

5.2 Conclusion on understanding and quantifying technology cost reduction drivers'

Chapter 2 reveals the complex dynamics in an energy technology innovation system to drive cost reduction. Multiple drivers and how they relate along the innovation stages of development are identified. The role of spillover of knowledge between stakeholders, the outputs of research activities and dynamics in the markets in term of supply-chain and demand availability are all factors influencing costs but the literature struggle to quantify them.

In Chapter 3 a detailed model has been developed to quantify as learning by-researching, learning by-doing, market dynamics and supply chain dynamics drivers with a BUCMs for the first time. As is shown with the specific case of onshore wind, one-factor learning curve will not be able to explain the multiple drivers cost reduction elements. Hence, if the mechanisms driving cost reduction are to be investigated, a multiple driver analysis is required. The case study of onshore wind focuses on the full-commercialization stage of development and shows that while learning by-deployment remains the most relevant driver, also drivers related to the market dynamics and supply-chain have a relevant impact on cost reduction. This analysis allows the investigation of four distinctive drivers, and furthermore, to relate with the causes of cost reduction such as market material prices, material utilization, and employees productivity, which can be useful for decision makers to understand what it is the major driver cost reduction and how policy can influence it.

In order to enrich the understanding and quantify driver of cost reduction, this thesis recommends overcoming the limits of one-factor learning curve method by focusing on developing multiple drivers analysed. Moreover, it is necessary to investigate which variables best describe each conceptual driver of cost reduction investigated within technology innovation framework, thus within each stage of development, in order to simplify the understanding of these dynamics for decision makers.

5.3 Conclusion on accelerating technology cost reduction

Energy technology innovation policies can be addressed at different stages of development, varying from those allocated once deployment is achieved to those up-stream focused on technological improvements implementations. This thesis provided a looking forward contribution in Chapter 4, it revealed that technology innovation policies which seek to accelerate renewable energy technologies to achieve low-carbon future should have a broad focus and take into account different elements involved in the energy technology innovation system according at each stages of development, enlarging to the needs in market and supply chain, policy and regulation alignments, and supporting technologies innovation.

The investigation of historical innovation showed a more coherent representation of multiple drivers of cost reductions along the stages of development, how technology innovation advanced and the specific innovation challenges required in the energy system to enhance emerging energy technologies. This thesis shows a number of relevant conclusions in this regard for wave energy in Ireland. These innovation needs identified highlight specific areas of interest to devise effective policies or strategies which are not only limited to industry and learning by-doing.

- Standard design is crucial to achieve deployment, which means overcoming the diversity of operating wave environments reflected in the multitude of different designs investigated. It is important to understand the short-term role of local niche markets, their potential in contributing to both technology standardization and technology unit scale-up for wave energy to compete with other technologies in the energy system. The potential of multiple standard designs according to market and wave environment should be evaluated for this technology.
- Physical and knowledge infrastructures are required in areas with high energy resource availability. Thus, policies need to attract stakeholders to investigate local markets, in order to guarantee the creation of knowledge clusters in the supply chain and balance of the system of the technology. Currently, the potential for a local supply chain of stakeholders is available in Ireland. The creation of cluster between stakeholders at the current stage of development of wave energy technology would allow the spillover of good practices and learning that may be useful for the diffusion in a niche market. Moreover, the development of physical infrastructures and a robust supply chain industry is a prerequisite to foster the

commercialization in the area and to achieve cost reduction, this innovation need will be of high interest in a near-term future to guarantee in the sized to technology port facilities, access and connection to HV grid and roads to reach the future ocean farm sites.

- National policy requires a balanced decarbonisation plan to clarify the potential role of different energy technologies in the market, and the electrification potential within the energy system. Wave energy penetration in the system would also dependent on the asset of the energy system. Thus, it is important that the decarbonisation plan does not obstruct any future technological development showing consistency, flexibility, responsive and capacity of adaptation.
- Policy regulation and market readiness is important to achieve deployment in the same way as technological readiness. Technology development must be accompanied by policy and regulation learning and development in order to avoid market halts and bottlenecks.

5.4 Future work

This thesis does not intend to be the only solution to the challenges of achieving a low-carbon future and much remains to be studied to understand the role of energy technology innovation to foster future emerging renewable technology development.

The energy technology innovation system is complex, and the development of models to analyse its attributes, as for example technology cost reduction, can increase this understanding. Moreover, in this way, the means to accelerate technology innovation can be investigated and a clear understanding will help to integrate innovation in energy system models, the main tool used to assist policy makers.

The work of this thesis could be further improved in relation to the following areas:

- A continued investigation of the role of technology innovation in technology cost reduction is required to deepen the understanding of multiple drivers of cost reduction and reduce the methodology uncertainties. Particularly the focus should be on drivers such as the spillover of knowledge, and supply-chain and market dynamics of which may highly influence technology cost reduction particularly once commercialization is achieved.

- This thesis is developed with an application of BUCM for onshore wind turbine costs, the use of this tool is relatively new in this field of energy technology innovation and it should be further developed and analysed. To improve the BUCM results and methodology the focus should be on increasing the number of quantifiable techno-economic variables into the cost equation of the model, which will allow increase the understanding of multiple driver disaggregation and quantification. To do so, an effort in data collection is required, data is usually limited, sparse and difficult to obtain. The development of an analysis at country level could help to identify specific variables to measure with the use of surveys targeting specific stakeholders in the field, while this would be too complex at global level. Moreover, this would allow the investigation of the differences between drivers in various markets.

- An application of BUCMs on wind energy prices (LCOE) could be a follow-up of this analysis. In this way the findings between these two analyses could be compared to identify how the drivers impact change with different cost metrics assumed. Moreover, a BUCM model developed could be applied to other renewable energy technologies, enhancing both differences between each technology type and parallelisms and similarity.

- The achievement of energy technology innovation is characterised not only from technology cost reduction but also from other elements such as technology improvements, demand increase, acceptance and market adaptation. It is important also to investigate the dynamics of these other elements to understand what enhances their success in the energy technology innovation system.

- The analysis of acceleration of cost reduction is done in this thesis using energy system modelling with exogenous learning combined with historical innovation approach. The mixed approach offers a solution to the difficulty to model innovation in energy system models. Due to the difficulty of the topic, research should proceed by supporting the role of sensitivity analysis and an integrated approach with qualitative innovation studies which will help understand that which cannot be explained by the model related to the role of technology innovation for future emerging renewable energy technologies. The complexity of dynamics behind cost reduction makes it complex to integrate multiple drivers in energy system modelling to provide a realistic and reliable representation.

- In the future, it is suggested to jointly collaborate within the energy system modelling communities to investigate the optimal solutions to integrate the different aspect of technology innovation, as for example starting from the implementation of simpler learning curves supported by external historical innovation approach and move then to more complex tools which better explain the role of disruptive technologies and innovation in modelling.

Annex I

ETSAP meeting Innovation Workshop report

The following annex describes the insights gained during the Innovation workshop organised for the 74th ETSAP meeting. This workshop is an implication of my thesis work, technology innovation is an interdisciplinary topic and the energy modellers community showed a high interest on this topic in the latest years. Energy technology innovation may influence the future energy system development; thus, modellers want to find solutions to better represent it in long-term energy system models. The current methodology used in ESOMs are highly simplified, with this workshop energy modellers and innovation practitioners were brought together to discuss and exchange expert opinions about this topic.

This workshop was organised thanks to the knowledge gained about technology innovation presented in chapter 2 and 3 and the insights were relevant to develop the methodology used in chapter 4. In chapter 4 technology innovation for emerging energy technologies is discussed by linking the innovation studies with energy system modelling.

I.1 Context

The 6th session on innovation during the 74th ETSAP Workshop was organised with the aim of bringing together innovation practitioners and experts within the energy systems modelling community. It was organised by the Energy Technology Systems Analysis Program (ETSAP) modelling community partners in collaboration with innovation experts from the International Renewable Energy Agency (IRENA). ETSAP – a Technology Collaboration Programme within the IEA – has as one of its main goals the investigation of solutions to advance knowledge in energy systems modelling platforms. IRENA is an intergovernmental organisation that supports countries in their transition to a sustainable energy future by providing cutting-edge information on innovative solutions to enable energy sector transformation.

Despite rapid growth in the installed capacity of wind power and solar-PV globally, overall decarbonisation of the energy system is still progressing slowly. There is a need to accelerate the low carbon energy transition to align with the rapid decarbonisation aims agreed in the Paris Agreement. Energy system optimization models (ESOM) are widely used to develop long-term decarbonisation pathways to inform climate and energy policy. At the same time, technology innovation has proven to be a driver of recent energy system decarbonisation progress and is likely to be instrumental in future energy system decarbonisation [6]. Therefore, two open questions are: how well do ESOMs capture the role of innovation and how should the impact of disruptive technologies and innovation solutions [255] – which are expected to play a key-role in a decarbonised future [256] – be represented?

I.2 Workshop objectives and format

The objectives of the workshop were to bring together sets of experts in long-term energy system modelling and innovation, to discuss the latest findings, barriers and open questions related to the representation of technology innovation in long-term energy system modelling. Topics covered included technology innovation concepts, current barriers and modelling limits, and some of the best available methods to overcome these issues. How innovation is measured, tracked and represented was also discussed. In addition, the workshop was used to present a range of recent undertaken projects, which dealt with the improvement of the representation of innovation in energy system modelling as part of the IRENA-CEM[11] campaign, MI actions[12], and IEA RD&D[13] program.

The format was a joint opening address from ETSAP and IRENA, a series of presentations on the frontiers of current knowledge, current modelling practices, and audience discussion. This workshop report adopts this structure and also adds summary and reflections on the presentations and discussion.

[11] Clean Energy Ministerial (CEM) is a forum of energy ministers of the world's key economies working together to accelerate the global clean energy transition. More information at: https://www.cleanenergyministerial.org/

[12] Mission Innovation (MI) is a global initiative announced after COP21 (2015) aiming to accelerate global clean energy innovation. More information at: http://mission-innovation.net/

[13] International Energy Agency (IEA)

I.3 Opening address

In their opening address, the two chairs of this session, Brian Ó Gallachóir (IEA-ETSAP) and Paul Durrant (IRENA), highlighted the current vision of technology innovation as encompassing modellers and innovation practitioners. It has previously been shown that the two worlds are missing a point of contact between the reality of technology innovation and what is being represented in energy systems modelling.

Technology innovation has been identified as one of the main push factors behind the implementation of renewable energy technologies in an energy system. Disruptive technologies and innovation solutions including the adoption of new financial and market models, artificial intelligence, and digitalization, are contributing to enabling an energy system transition towards a low carbon future [256]. Therefore, a question from innovation practitioners to energy system modellers is to what extent are these innovations currently reflected in long-term scenarios?

The perspective from the energy systems modelling community is to understand how to track technology innovation, how to measure it, and thus to understand which innovations in technology or business models should be reflected in long-term scenarios to investigate its implications.

At present, the state-of-art models do not consider disruptive innovation, however, some innovation elements are explored in the latest models. For example, modelling energy performance (i.e. capacity factors), and technology costs (e.g. investment costs) is in large part about the integration of technology innovation in long-term optimization energy system modelling. The current methods are not capable of describing the technology innovation impact on energy scenario results. Thus, were the limits of modelling and the opportunities to implement innovation discussed in the opening address.

I. 4 Presentations

I.4.1 Review of current knowledge

Current methodologies used to describe innovation in terms of technology cost reductions were shown, as well as the complexity of their implementation. Fionn Rogan (UCC)[14] presented a review of multi-factor learning curves, as discussed in the literature, showing the uncertainty of representing cost reduction with this multi-factor approach. In the literature, the one-factor learning curve method has been the most applied, but moving from one-factor learning curves to multi-factor learning curves, there is an increase of uncertainty regarding the choice of parameters to represent innovation elements and associated data gathering. The presentation showed that learning curves may vary at 1) different stages of development, 2) between global or local learning, and 3) for different technological components of a macro technology. Moving to multi-factor learning curves requires a better understanding of the myriad dynamics behind technology innovation. For example, with certain elements such as RD&D public support, the knowledge is split between the country, technologies or stakeholders; in addition to this, there is the impact of markets on cost reduction.

I. 4.2 Current modelling practice

Three examples of practices developed to find solutions to measure technology innovation were presented: Hans Christian Gils (DLR)[15], Uwe Remme (IEA)[16], Alessia Elia (UCC-IRENA)[17].

Hans Christian Gils described selected results of the RegMex project where different energy system models were compared and evaluated regarding their ability to take disruptive elements into account. The results of the projects allow defining a list of innovation elements, mostly considered disruptive innovation elements, and the main

[14] Elia, A.; Rogan, F.; Ó Gallachóir, B. - *From single-factor to multi-factor learning curves for modelling innovation – a review*. Link: https://www.slideshare.net/IEA-ETSAP/from-singlefactor-to-multifactor-learning-curves-for-modelling-innovation-a-review)

[15] Gils, H. C. - *Consideration of disruptive elements in energy system models*. Link: https://www.slideshare.net/IEA-ETSAP/consideration-of-disruptive-elements-in-energy-system-models

[16] Remme, U. – *Challenges in the modelling of experience curves.* Link: https://www.slideshare.net/IEA-ETSAP/limitations-in-representing-innovation-in-energy-systems-models

[17] Elia, A.; Taylor, M.; Rogan, F.; Ó Gallachóir, B. - *Deepening cost analysis for Onshore Wind Technology*. Link: https://www.slideshare.net/IEA-ETSAP/deepening-cost-analysis-for-onshore-wind-technology

parameters of a long-term energy system model that might be influenced by these innovation elements. For example, “shortage or cost explosion of structural materials” innovation elements may influence technology costs. Still, these disruptive elements were not implemented in the energy system models and linked with the parameters.

Uwe Remme presented the current approach used at IEA to include in the IEA-ETP model technology innovation through a soft-linked one-factor learning curve. Moreover, he discussed some of the challenges in the use of learning curves and approaches to address them, such as component-wise learning, global versus local learning and the limited availability of empirical data for new technologies with little deployment so far. Uwe also talked about the endogenous representation of one-factor learning curves in energy system models, pointing out some new formulation approaches with some potential computational benefits compared to the traditional formulations.

Alessia Elia discussed an alternative method to investigate onshore wind cost reduction, stepping away from the most common use of a learning curve. The method is based on a cost disaggregation bottom-up cost model, and the aim is to identify and understand how costs are influenced along the stages of development of a technology and which are the main elements influencing them. For example, structural materials, labour salary, industrial progresses, the cost related to the installation and transports and the effects of demand markets were explored.

I. 4.3 Innovation projects

During the workshop, three innovation based projects being undertaken by three different organizations were presented. The projects were related to long-term energy system modelling to improve the tool and reduce the uncertainty in order to promote their adoption.

The first project is the new IRENA-CEM campaign “long-term energy scenarios (LTES) for clean energy transition” presented by Paul Durrant[18]. The project aimed to encourage the use of models and to identify gaps and improvements required through the share of the use between different modeller groups.

[18] Durrant, P. - *IRENA-ETSAP – Innovation in long term energy scenarios.* Link: https://www.slideshare.net/IEA-ETSAP/irena-cem-campaign-and-innovation

The second project described the work done on energy innovation from the International Energy Agency (IEA) presented by Uwe Remme. This included the tracking and collection of RD&D expenditures and the progression of clean energy technology in the IEA's annual Tracking Clean Energy Progress report as well as the identification of innovation gaps, to provide a comprehensive picture of the current stages of development for different technologies.

Daniele Poponi (Directorate General for Research & Innovation, European Commission)[19] presented the 'Tracking Progress' activities of the Mission Innovation initiative (MI). Four related work strands are currently being implemented: (a) Tracking the Impact of MI (e.g. MI members are requested to submit information and data related to investments and national plans through "MI country surveys"; (b) Enhancing existing data collection on government spending for energy RD&D (E.g. through capacity building activities); (c) Tracking private-sector investments (e.g. e.g., by exchanging information to improve understanding of clean energy innovation needs of the corporate sector) and (d) Tracking Overall Progress to Accelerate Clean Energy Innovation (e.g. through the development of an indicator framework based on innovation outputs).

I.5 Summary of presentations

The presentations highlighted the limits of long-term optimization energy system modelling, which included many aspects of energy technology innovation, but also the limited understanding of the elements driving technology innovation. Furthermore, the presentations showed the current difficulties in implementing endogenous cost reduction with learning curves and modelling disruptive elements of innovation. Through a show-of-hands informal poll, it was revealed that most of the participants in the audience did not endogenously implement the one-factor learning curve in energy system modelling, or any other tool. Moreover, it remains unclear how innovation can be adequately modelled. Learning curves are a limited methodology and are only related to costs, but not to other parameters that could be affected by the innovation, such as technology parameters and energy demand, as discussed in Hans Christian Gils's presentation.

[19] Poponi D. - *New approaches to understanding innovation*. Link: https://www.slideshare.net/IEA-ETSAP/new-approaches-to-understanding-innovation

The three projects underway with IRENA-CEM, IEA and the European Commission are a starting point to allow for a better implementation of innovation in energy system modelling by including and tracking the innovation underway before market deployment. The goal of these projects is to better represent the path of emerging energy technologies and any disruptive innovation influencing them. Still, most of the disruptive technologies, such as digitalization, are not represented in modelling. The outputs from the RegMex project shows an initial attempt to discuss disruptive elements that may influence the innovation of emerging energy technologies. Furthermore, it can investigate the parameters that could be used to implement innovation impact on energy system modelling.

I.6 Reflection on presentations

The presentations revealed two points that are missing from the current state-of-art energy systems modelling:

1. It is not clear within the energy system modeller community how to track technology innovation.
    a. The most credited method to capture the innovation is the learning curves, but the one-factor learning curves are too simplistic, while multi-factor learning curves are uncertain in the research community. Moreover, it is complex to gather the required data. When we compare this method with the innovation practitioner community, as the IRENA experts, we can conclude that innovation involves a myriad of disruptive elements. These disruptive innovation elements are related to technology changes or to system changings such as digitalization or the impact of the industry 4.0.
    b. Technology innovation does not only take technology cost reduction into account but also other technical parameters, and energy system elements. The picture is complex to gather and to model.
2. A method to implement the impact of innovation in long-term energy system modelling is missing.
    a. The most widely used approach is to discuss technology innovation in terms of impact on cost reduction with one-factor learning curves. Method of implementing more than the one-factor learning curve is imprecise, and both

of these learning-curve tools are limited in representing technology innovation in energy system modelling.

b. Many of the disruptive innovation elements identified by innovation practitioners do not find representation in the current state of energy modelling, and neither can all of them influence cost reduction. They may be responsible for technology performance improvements and deployment but there is no representation of these effects in the models.

I.7 Audience Discussion

I.7.1 Chaired Q&A

After the presentation, three opening questions were proposed to the audience regarding the gaps and what is missing in long-term energy scenarios:

1) Which innovations in technology or business models should be reflected in long-term scenarios of clean energy transitions to 2030-2050?

2) To what extent are those innovations currently reflected in scenarios?

3) In general how can long-term scenarios be made more relevant to business planning and policy making under large innovation-related uncertainties?

I.7.1.1 Which innovations in technology or business models should be reflected in long-term scenarios of clean energy transitions to 2030-2050?

The answers from the first question are aggregated into 5 categories (Table I-1): new emergent innovative technologies, inclusion of additional characteristics of energy technologies to map their innovation path, innovative business model paths, innovative policy, and the representation of consumer behaviour. The participant agreed that the current energy system models do not include all the proposed innovation types, and they risk providing an unrealistic representation of the medium term of the upcoming future (2030-2050). Models do not depict the impact of emergent and innovative technologies, attributes, policy, consumer behaviour and business model all together. This creates space for future ideas regarding what should be included in modelling, ensuring an integrated innovation.

Table I-1. Answer from the audience question 1

Innovation to implement in long-term scenarios

Energy Technology integration	Business model	Innovation Policy	Consumer behaviour	Technology attributes
Smart grid decentralised production Autonomous drones CCS Multi-purpose batteries storages Shared mobility Autonomous vehicles Bio-materials Ocean energy Nuclear fusion Micro-grid Off-grid Cellular solutions	Peer to peer trading Circular economies business models	Mechanisms to incentivise lifestyle changes	Change in lifestyle Public ownership / acceptance Alternative business income (Facebook advertising)	CO_2 and resource recycling Reduction in costs Digitalisation impact on technologies (one device manages more services) EV chargers pattern management Grid and infrastructures flexibility

I.7.1.2 To what extent are those innovations currently reflected in different scenarios?

The energy modelling community agrees that innovation is mainly included indirectly with the adoption of exogenous variables, such as adjusting the parameters describing the existing technologies. However, the emergent innovation aspects highlighted in the previous question are still missing, as well as the consideration of innovation impacts in multiple parameters of the model. Moreover, current modelling norms do not allow innovative elements effects to link with the future technology deployment.

The main issues highlighted from the audience in the discussion are:

i. Innovation is represented via specific parameters, such as costs and technology technical parameters, but a reflection on the impact of other innovation element is missing. Technology learning consistently underestimated for renewables.

ii. Innovation is introduced in an exogenous and simplistic way and is applied on few technologies, while missing the comprehensive picture, which leads to biased results. The only way to investigate the variation of the level of innovation is through a sensitivity analysis of the parameters used, such as costs and capacity factors. This gives rise to the question as to whether innovation is an input or whether it should be endogenously generated in the model. So far, it has been assumed that technologies will achieve the specific innovation, and the parameters are exogenously set up in the model.

iii. Disruptive innovation is not a gradual change of parameters, but a drastic step-change. It is not currently reflected in the models. New emergent innovative technologies are not represented either, with the exception of CCS technologies. Therefore, the signs of a totally different trajectory cannot be represented because emergent technologies and disruptive innovation do not exist in the model.

iv. The current models do not take into account the changes in service demand with the introduction of disruptive innovation. The fact that most models employ perfect foresight creates modelling problems.

I.7.1.3 In general, how can long-term scenarios be made more relevant to business planning and policy making under large innovation-related uncertainties?

In conclusion, the last question underlined the main points that would help energy system models to become more relevant for business planning and policy making. The following actions were suggested:

1) Include

- Different time horizons with alignment to different business cycles or political electoral cycles.
- Near-term measures and transition strategies.
- Co-production between resources, e.g.: future bio-fuel plants, co-electrolysis and bioenergy.
- Speculative technologies, even if controversial.

2) Adopt

- Stochastic methods (Montecarlo analysis setup).
- Black swan scenario/Unknown-unknown scenario.
- Wide spread of scenarios with contrasting scenarios.

3) Combine with

- Historical lessons, i.e. what went well, and what didn't.
- Use of historical innovation examples to illustrate the dynamics.
- Different modelling approaches to provide complementary insights on similar scenarios.
- Better visualization of results: illustrating the required technologies, resource constraints and sector linkage.

4) Clarify

- Scenarios that are not predictable but indicative and based on system constraints and assumptions.
- The uncertainties with the scenarios analysed and the appropriate way to work on it. More transparency on the constraints.

I.8 Reflection on audience discussion

At the end of this second audience question, the discussion nurtured new ideas which could be beneficial to solve the issues on integration of innovation in modelling. The following 4 points were highlighted by people in the audience as some of the main points to focus on in the near future:

1. Aware of the issues behind learning curve tools, the inclusion of more elements of disruptive innovation could require even more complex application and create more uncertainty without adding additional accuracy or insights. It is suggested to investigate to what extent it is important to introduce complicated innovation in the model, and where is the trade-off between complexity and results generated. Due to a lack of data, modellers should perhaps start with one-factor learning curves before analysing more complex methods. Very few people in the audience are using endogenous learning curves in the modelling at the moment, and the representation is flawed in the case of one-factor. There should be modelling exercises to incorporate one and multi-factor learning curves, or other methods between modellers, so that they can gain more experience using endogenous innovation and then be able share their experiences and findings within the ETSAP community.

2. Scenario sensitivity analysis could be a less complex and more certain form to capture some extreme and large variations related to the innovation impact that normally with the current models are not captured. Exploratory scenarios could be developed, such as, for example, how much cost reduction is required, so that disruptive technologies can compete with the current one, and how much deployment or investment is necessary to achieve that cost reduction.

3. To understand how to model disruptive technologies, most of the 2040 disruptive technologies could still not exist. For example, how to design a technology that will substitute most incumbents and induce energy service demand changes in short-time in the model, e.g. the smartphone. If technologies that are free riders, without any learning imposed, they appear late in the model horizon. Modellers should consider additional constraints as growth rate constraints, investment spending and anticipated costs, given by how that technology might appear without considering RD&D costs. Also, in this case scenario analysis could assess demand disruption.

4. An ex-post analysis is also important to understand why cost reduction happened and accelerated in the case of well-known renewable energy technologies such as solar-PV and onshore wind. In order to understand if those assumptions taken to calculate cost reductions in the past can be used in the future. The audience agreed on the importance on using right assumption because these are used to inform government policies and markets. Therefore, a wrong assumption could lead to misinformation. Better understanding of the dynamics pushing technology success in a system is required to catch the learning and the lack of improvement in the past. A combination of factors may be specific to wind, thus it is necessary to understand whether that pattern is likely to repeat again and how it might impact in the same way for another technology. Analysis of historical technology innovation paths could also explain what went wrong, e.g. offshore wind slow down – Risk ratio parameters of investment that can change the amount of investments done in a technology.

I.9 Conclusions

The workshop revealed important questions that are a starting point for further work in this field. They can be summarised in three main points (Figure I-1); firstly, it is necessary to develop an explorative collaboration in the analysis of learning curve in models. In order to learn from each other's experiences, to understand the limits of the modelling in including learning curves, which is the border to the models capability, and which elements driving technology innovation can be included both exogenously or endogenously. The final goal would be reaching a level that determines some understanding as to whether the results are imperfect and why, rather than some unknown that we are trying to represent describing a one-factor learning curve.

Secondly, to focus the analysis on the effect of one technology and translate them to emerging technologies. For example, are cost reductions on wind transferable to other technologies? Understanding how to use information from the past or from incumbent technologies to more efficiently inform what might happen in the future is vital, and should not just translate to a learning rate factor. Working with exogenous parameters is an appropriate method, but there is need of sensitivity analysis of scenarios and to obtain a better understanding of the dynamics of what has happened, to learn how to transfer information from one technology to another.

Finally, continuing the investigation of disruptive technologies and elements and explorative exercises to include them in the modelling in the future. Quantifying something that it is not well understood such as technology innovation dynamics and the impact of disruptive elements.

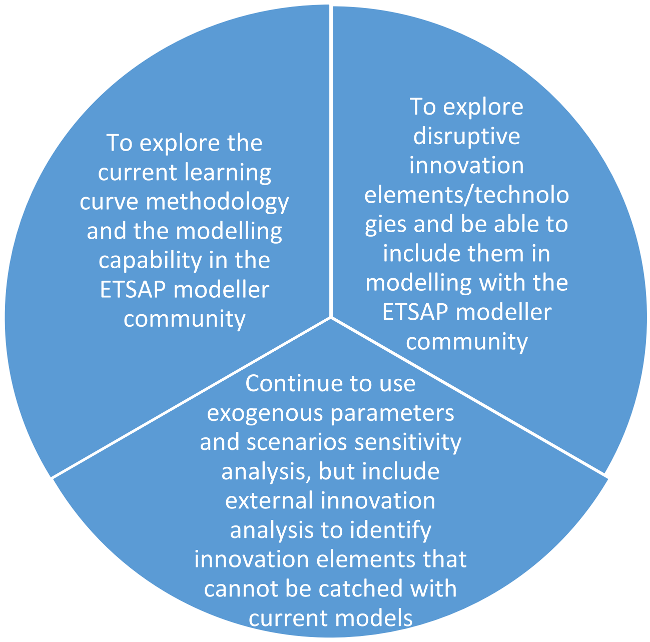


Figure I-0-1. Conclusion remarks

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Appendix A

This appendix serves to provide results from MFLCs literature reviewed in Chapter 2.

Table A-1. Onshore MFLCs reviewed results

Papers	**Learning drivers**	**Dependent cost variable**	**Period start**	**Period End**	**location**	**R^2**	**learning by doing**	**learning by researching**	**Economies of scale**	**Knowledge spillover**	**Supply-chain dynamics**	**Demand market dynamics**
[257]	KS(geo): Cumulative global capacity installed. ES: Wind turbine size. LBR: knowledge stock evaluated with soft-linked RD&D model, country dummy variables	Investment costs	1986	2002	DK-UK-SP-SW-DE	0.88	20%	21%	n.s.s.	KS-geo LBD: 17% KS-geo LBR: n.s.s.		
[147]	LBD: Cumulative capacity installed. IM-S: steel material market price	Investment costs	1991	2008	Europe	0.37				KS-geo LBD: 8.4%	Steel: -44%	
[147]	LBD: Cumulative national capacity installed KS(geo): cumulative global capacity installed. IM-S: Steel material market price	Investment costs	1991	2008	Europe	0.364	1%			KS-geo LBD: 6.9%	Steel:-43%	
[147]	KS(geo): Cum. Global capacity. IM-S: steel price. LBR: Patents knowledge stock	Investment costs	1991	2008	Europe	0.385		5%		KS-geo LBD: 5.6%	Steel: -41%	

[147]	KS(geo): Cumulative global capacity. DM(policy): feed-in tariff. LBR: Patents knowledge stock. IM-S: steel material market price	Investment costs	1991	2008	Europe	0.434		5%		KS-geo LBD: 1.2	Steel:-42%	
[140]	DM(policy): Feed-in tariff, local content requirement, Secondary CER price. DM(resources quality): Capacity Factor wind turbines DM(competitors): Wind power/total power generated, total electricity demand in the region, cumulative capacity installed of steam turbine, cumulative capacity installed of hydropower. ES: Global size turbine. KS(ind): Developers and manufactures ownership dummy variables	Investment costs	2005	2012	China	n/a			n.s.s.			Feed-in Tariff:-15% Local content req.: 0.4% Share wind/total power: 5%
[140]	LBD: Developers cumulative capacity installed, Manufactures cumulative capacity installed. LBR: Patents knowledge stock. DM(policy): Feed-in tariff, local content	Investment costs	2005	2012	China	n/a	Only manufactures: n.s.s.	n.s.s.	n.s.s.	KS(ind) joint learning developers-manufactures : -0.6%		Feed-in Tariff:-15% Local content

	requirement, Secondary CER price. DM(resources quality): Capacity Factor wind turbines DM(competitors):Wind power/total power generated, total electricity demand in the region, cumulative capacity installed of steam turbine, cumulative capacity installed of hydropower. ES: Global turbine size. KS(ind): Developers and manufactures ownership dummy variables. Cum. capacity installed in common between developer and manufactures.						Only developer s: 0.8%					req.: 0.27% Share wind/total power: 5%
[110]	LBD: Cumulative capacity installed. ES: Wind power generation level	Investment costs	1981	1995	Global	0.63	18%		1			Feed-in Tariff:-15%
[110]	LBD: Cumulative capacity installed. ES: Wind power generation level	Investment costs	1981	1995	Global	0.89	17%		0.88			
[141]	LBD: Cumulative capacity installed. LBR: Public RD&D, Patents	Investment costs	1980	1998	Global	n/a	13%	27%				

[150]	LBD: Cumulative capacity installed. LBR: RD&D (Public and Private) knowledge stock. ES: Wind power generation level	Investment costs	1979	1997	Global	0.985	19%	17%	0.936			
[78]	LBD: Cumulative capacity installed. LBR: RD&D (public and private) knowledge stock. ES: Wind power generation level	Investment costs	1979	1997	Global	0.99	26%	44%	0.57			
[78]	LBD: Cumulative capacity installed. LBR: RD&D (public and private) knowledge stock. ES: Wind power generation level	Investment costs	1979	1997	Global	0.99	31%	33%	0.55			
[78]	LBD: Cumulative capacity installed. LBR: RD&D (public and private) knowledge stock. ES: Wind power generation level. Adjustment variables: sales of power generation, global crude oil prices	Investment costs	1979	1997	Global	0.99	27%	20%	0.56			
[78]	LBD: Cumulative installed capacity. LBR: RD&D (public and private) knowledge stock.	Investment costs	1979	1997	Global	0.99	n.s.s.	n.s.s.	0.49			

	ES: Wind power generation level. Adjustment variables: sales of power generation, global crude oil prices											
[148]	LBD: Cumulative electricity generated. DM(policy): adjustment of electricity prices with feed-In tariff index	Electricity price	2002	2009	South Korea	0	0.50%					
[41]	LBD: Cumulative capacity installed. LBR: RD&D knowledge stock. KS(geo): dummy country variables	Investment costs	1986	2000	UK , Germany, Denmark	0.72	5,40%	13%				
[135]	LBD: Cumulative capacity installed. LBR: RD&D knowledge stock	Investment costs	1971	1997	Global	0.947	14,20%	18%				
[142]	LBD: Cumulative capacity installed. LBR: RD&D knowledge stock	Investment costs	1971	1997	Global	0.8	10%	10%				
[146]	LBD: Cumulative capacity installed. DM(resource quality): capacity factor, regional dummy. IM-S: steel index. MD: exchange rate.	Investment costs	2005	2011	India	0.566	17%				Steel: -27.70% Exchange rate: -23%	Cap. Factor: 40%

[146]	LBD: Cumulative capacity installed. DM(resources quality): capacity factor, regional dummy. IM-S: plant costs index, exchange rate.	Investment costs	2005	2011	India	0.56	12%				Plant costs:-51% Exchange rate: -19%	Cap. Factor: 40%
[146]	LBD: Cumulative capacity installed. DM(resources quality): capacity factor, regional dummy. IM-: steel material price index, exchange rate. TIME TREND	Investment costs	2005	2011	India	0.566	17%				Steel: -27% Exchange rate: -23%	Cap. Factor: 40%
[146]	LBD: Cumulative capacity installed. DM(resources quality): capacity factor, regional dummy. IM-S: steel material price index, plant costs index, exchange rate. TIME TREND	Investment costs	2005	2011	India	0.515					Steel: -44% Exchange rate: -15%	Cap. Factor: 40%
[146]	LBD: Cumulative capacity installed, ES: wind power generations	Electricity generation costs	2005	2011	India	0.239	18%		n.s.s.			
[146]	LBD: Cumulative capacity installed. DM(resources quality): capacity factor, regional dummy. IM-S steel material price index, exchange rate. ES: project capacity	Electricity generation costs	2005	2011	India	0.679	18%		1.24		Steel: -31% Exchange rate: -27%	Cap. Factor: 26%

[146]	LBD: Cumulative capacity installed. DM(resources quality): capacity factor, regional dummy. IM-S: plant costs index, exchange rate. ES: project capacity	Electricity generation costs	2005	2011	India	0.667	13%		n.s.s.		Plant costs:-48% Exchange rate: -22%	Cap. Factor: 26%
[146]	LBD: Cumulative capacity installed. DM(resources quality) capacity factor, regional dummy. IM-S steel material price index, exchange rate. ES: project capacity. TIME TREND	Electricity generation costs	2005	2011	India	0.679	18%		1.24		Steel: -32% Exchange rate:-27.90%	Cap. Factor: 26%
[146]	LBD: Cumulative capacity installed. DM(resources quality): capacity factor, regional dummy. IM-S steel material price index, plant costs index. MD: exchange rate. ES: wind farm project capacity. TIME TREND	Electricity generation costs	2005	2011	India	0.641			n.s.s.		Steel: -48% Exchange rate: -19%	Cap. Factor: 26%
[88]	KS(geo): Cumulative global capacity installed, Public Danish RD&D fundings	Electricity generation costs	-	-	Sweden	0.86				KS-geo LBD: 23% KS-geo LBR:74%		

[24]	LBD: Cumulative capacity installed. LBR: tech adoption. Joint learning LBD-LBR. ES: wind farm scale. KS (ind): localization rate. IM-S steel price. DM(resources quality): wind quality dummies	Electricity generation costs	2003	2007	China	0.633	4%	Joint to LBD	1.1	Loc. Rate: 20%	Steel:-18%	
[24]	LBD: Cumulative capacity installed. LBR: technology adoption. Joint-learning LBD-LBR. ES: wind farm scale. KS (ind): localization rate. IM-S steel price. DM(resources quality): wind quality dummies. TIME TREND	Electricity generation costs	2003	2007	China	0.6969	4%	Joint to LBD	1.15	Loc. Rate: 11%		
[24]	LBD: Cumulative capacity installed. LBR: technology adoption. Joint-learning LBD-LBR. ES: wind farm scale. KS(ind): localization rate, company own installed capacity, other company installed capacity - firm market share dummy (LARGE SHARE). IM-S steel price. DM(resources quality): wind quality dummies	Electricity generation costs	2003	2007	China	0.636	5%	Joint to LBD	1.11	Loc. Rate: 21%	Steel: -18.20%	

[24]	LBD: Cumulative capacity installed. LBR: technology adoption. Joint-learning LBD-LBR. ES: wind farm scale. KS (ind): localization rate, firm entity dummy (SOE) - firm experience dummy (NEW, MEDIUM). DM(resources quality): wind quality dummies. TIME TREND	Electricity costs	2003	2007	China	0.7	5%	Joint to LBD	1.156	Loc. Rate: 11%		
[24]	LBD: Cumulative capacity installed. LBR: technology adoption. Joint-learning LBD-LBR. ES: wind farm scale. KS (ind): localization rate, firm entity dummy (SOE) - firm experience dummy (NEW, MEDIUM). IM-material steel price. DM(resources quality): wind quality dummies	Electricity generation costs	2003	2007	China	0.646	5%	Joint to LBD	1.098	Loc. Rate: 20% KS-ind: (others firms): 5.05% KS-ind: (only large share firms): -4.7%	Steel:-18%	
[153]	LBD: Cumulative capacity installed. DM(policy): feed-in price. DM(competitors): coal price. LBR: RD&D knowledge stock. ES wind energy generation level. KS(geo): dummy country variables	Investment costs	1989	2000	DK-UK-SP-DE	0.89	3%	13%	1.01			Feed-in Tariff:-11%

[80]	LBD: Cumulative capacity installed. KS(geo): dummy country variables. TIME TREND	Investment costs	1986	2000	DK-UK-SP-DE	0.78	3%					
[80]	LBD: Cumulative capacity installed. KS(geo): dummy country variables. TIME TREND	Investment costs	1992	2000	DK-UK-SP-DE	0.81	n.s.s.					
[80]	LBD: Cumulative wind energy production. KS(geo): dummy country variables. TIME TREND	Investment costs	1986	2000	DK-UK-SP-DE	0.79	5%					
[80]	LBD: Cumulative capacity installed. SE: Wind energy generation level. KS(geo): dummy country variables. TIME TREND	Investment costs	1986	2000	DK-UK-SP-DE	0.79	n.s.s.		1.08			
[80]	LBD: Cumulative capacity installed. LBR: RD&D expenditures. KS(geo): dummy country variables. TIME TREND	Investment costs	1986	2000	DK-UK-SP-DE	0.79	3%	n.s.s.				
[80]	LBD: Cumulative capacity installed. LBR: RD&D (public) knowledge stock, KS(geo): dummy country variables. TIME TREND	Investment costs	1986	2000	DK-UK-SP-DE	0.79	3%	n.s.s.				

[80]	LBD: Cumulative capacity installed. LBR: RD&D (public) knowledge stock. SE: Wind energy generation level. KS(geo): dummy country variables. TIME TREND	Investment costs	1986	2000	DK-UK-SP-DE	0.8	n.s.s	n.s.s.	n.s.s.			
[80]	LBD: Cumulative capacity installed. LBR:RD&D knowledge stock. SE: wind energy generation level. PS: FEED-IN PRICE. TIME TREND	Investment costs	1986	2000	DK-UK-SP-DE	0.83	3%	n.s.s.	n.s.s.			Feed-in Tariff: -11%
[80]	LBD: Cumulative capacity installed. Adjustment of LBD with: coal prices, electricity prices. TIME TREND	Investment costs	1986	2000	DK-UK-SP-DE	0.96	8%					
[80]	LBD: Cumulative capacity installed. LBR: RD&D knowledge stock. Adjustment of LBD with: coal prices, electricity prices. TIME TREND	Investment costs	1986	2000	DK-UK-SP-DE	0.96	7%	n.s.s.				
[80]	LBD: Cumulative capacity installed. LBR: RD&D knowledge stock.SE: wind energy generation level.	Investment costs	1986	2000	DK-UK-SP-DE	0.96	7%	n.s.s.	n.s.s.			

	Adjustment of LBD with: coal prices, electricity prices. TIME TREND											
[80]	LBD: Cumulative capacity installed. LBR: RD&D knowledge stock.SE: wind energy generation level. DM(policy): Feed-In tariff. Adjustment of LBD with: coal prices, electricity prices (. TIME TREND	Investment costs	1986	2000	DK-UK-SP-DE	0.89	3%	n.s.s.	n.s.s.			Feed-in Tariff:-25%
[152]	LBD: Cumulative capacity installed. Interference variables: steel price index, oil price index.	Investment costs	2000	2010	Taiwan	0.871	-11%					
[124]	LBD: Cumulative electricity generation. Adjustments data considering wind quality effect with capacity factor	Electricity generation costs	1990	2015	US	n/a	10%					
[124]	LBD: Cumulative electricity generation, Adjustments data considering wind quality effect with capacity factor. Adjustment data with exchange rate	Electricity generation costs	1990	2015	US	n/a	10%					

	fluctuation, and fluctuation of material prices.											
[149]	LBD: Cumulative capacity installed. DM: plant load capacity factor	Investment costs	2004	2011	China	0.65	4%					
[42]	LBD: Cumulative capacity installed. LBR: patent knowledge stock. SE: wind farm size. IM-S: steel and fiberglass prices, labour and capital prices (as interest of loans in 5 years return)	Investment costs	1998	2012	China	0.98	9%	10%	0.91		Steel: -56% Fiber/resin: -5.1% Plant costs: -41.6%	
[42]	LBD: Cumulative capacity installed. LBR: patent knowledge stock. SE: wind farm size. IM-S: steel and fiberglass material market prices, labour and capital prices (as interest of loans in 5 years return)	Investment costs	1998	2010	China	0.99	7%	9%	0.96		Steel: -50% Fiber/resin: -4.8% Plant costs: -57.4%	
[42]	LBD Cumulative capacity installed. LBR: patent knowledge stock. SE: turbine quantity. IM-S: steel and fiberglass material market prices, labour and capital prices	Investment costs	1998	2012	China	0.99	9%	11%	0.9		Steel: -60% Fiber/resin :-4.6% Plant costs:-40%	

	(as interest of loans in 5 years return)											
[42]	LBD: Cumulative capacity installed. LBR: patent knowledge stock. SE: turbine quantity. IM: steel and fiberglass material market prices, labour and capital prices (as interest of loans in 5 years return)	Investment costs	1998	2010	China	0.99	8%	10%	0.96		Steel:-49% Fibreglass/ resin: -5% Plant costs: -58%	
[42]	LBD: Cumulative capacity installed. LBR: patent knowledge stock. SE: nameplate turbine. IM: steel and fiberglass material market prices, labour and capital prices (as interest of loans in 5 years return)	Investment costs	1998	2012	China	0.98	8%	7%	1.145		Steel:-42.5% Fiber/resin :-5.4% Plant costs:-52.4%	
[42]	LBD: Cumulative capacity installed. LBR: patent knowledge stock. SE: nameplate turbine. IM: steel and fiberglass material market prices, labour and capital prices (as interest of loans in 5 years return)	Investment costs	1998	2010	China	0.98	7%	9%	1.09		Steel: -46% Fiber/resin :-4.7% Plant costs:-60%	

[52]	LBD: dummy variable as year of wind farm completion, cumulative installed capacity. ES: Wind farm capacity, nameplate turbine. DM(resources quality): capacity factor. IM-S: construction costs index DM(competitors): California installation dummy. DM(policy): production tax credit	Electricity generation costs	1999	2006	US	0.736	n.s.s.		1.07 Nameplate turbine : n.s.s.		n.s.s.	Cap. Factor:38 %
[52]	LBD: Cumulative capacity installed. ES: Wind farm capacity, nameplate turbine. DM(resources quality) capacity factor. IM-S: construction costs index. DM(competitors): California installation dummy. DM(policy): production tax credit	Electricity generation costs	1999	2006	US	0.658	n.s.s.		1.07 Nameplate turbine : n.s.s.		n.s.s.	Cap. Factor:42 %
[143]	LBD: Cumulative capacity installed. LBR Public R&D	Investment costs	1992	2012	Global	0.839	2%	3.4%				
[143]	LBD: Cumulative capacity installed. LBR Public R&D	Investment costs	1992	2012	Global	0.799	3.8%	n.s.s.				
[145]	LBD: Cumulative capacity installed. LBR: Public R&D	Investment costs	2009	2016	US	0.974	17%	37%				

Notes:

a) In knowledge spillovers (KS) and demand market (DM) column only the significant results are reported. If no results is reported for a MFLC that includes these drivers it means that the results are not statistically significant
b) Economies of scale results are referred to return to scale parameter.
c) Results for dummy variables parameters are not reported.
d) "Investment costs" covers all the cost variables expressed per kW units. Variables as "installation costs", "turn-key costs", "wind turbine prices", "capital costs", "technology costs". Studies provide limited information about their cost elements and definitions and what is taken into account in their cost variables. There is not distinction between cost and price variables.
e) "Electricity generation cost" refers to "LCOE" and "electricity prices". There is not distinction between cost and price variables.
f) Geographical domain is referred to the cost variable in the MFLC
g) Knowledge stock refers to the annual RD&D expenditures by taking into account the depreciation of knowledge and the time-lag from between funded year and implementation.
h) For each regression model developed in the literature review papers different statistical tests are run in order to develop a significant analysis with the dataset available. Each paper shows its descriptive statistic tables together with the results, here we reported only the result of the coefficient of determination (R^2) found for each learning curve, more information is available in the papers.

Table A-2. Solar-PV MFLCs reviewed results

Papers	**Learning drivers**	**dependent cost variable**	**period start**	**period end**	**location**	**R^2**	**learning by-doing**	**learning by-researching**	**economies of scale**	**supply-chain dynamics**	**demand market dynamics**
[161]	LBD: Cumulative capacity installed. IM-S: Silicon prices	Module prices	1990	2011	Global	n/a	21%			-30%	
[157]	LBD: power generation. LBR: Knowledge stock (RD&D expenditures)	Electricity generation costs	2004	2011	South Korea	0.958	2%	5%			
[110]	LBD: Cumulative capacity installed. ES: solar power generation level	Module costs	1976	1994	Global		9%		1		
[110]	LBD: Cum capacity installed ES: solar power generation level	Module costs	1976	1994	Global		28%		0.88		
[150]	LBD: Cumulative capacity installed. LBR: Knowledge stock (RD&D expenditures - Public, Private). SE: solar power generation level	Technology costs	-	-	Global	0.54	4%	4%	0.871		
[150]	LBD: Cumulative capacity installed. LBR: Knowledge stock (RD&D expenditures - Public, Private). ES: solar power generation level	Technology costs	-		Global	0.78	5%	4%	0.864		
[78]	LBD: Cumulative capacity installed. LBR: Knowledge stock (RD&D expenditures - Public,	Technology costs (Inv. Costs for technology)	1977	1997	Global	0.78	7%	1%	0.94		

	Private). ES: solar power generation level										
[78]	LBD: Cumulative capacity installed. LBR: Knowledge stock (RD&D expenditures - Public, Private). ES: solar power generation level. TIME TREND	Technology costs (Inv. Costs for technology)	1977	1997	Global	0.8	n.s.s.	4%	n.s.s.		
[78]	LBD: Cumulative capacity installed. LBR: Knowledge stock (RD&D expenditures - Public, Private). ES: solar power generation level	Technology costs (Inv. Costs for technology)	1980	1997	Global	0.97	2%	3%	0.95		
[78]	LBD: Cumulative capacity installed. LBR: Knowledge stock (RD&D expenditures - Public, Private). ES: solar power generation level. TIME TREND	Technology costs (Inv. Costs for technology)	1980	1997	Global	0.96	2%	3%	0.93		
[148]	LBD: Cumulative electricity generated. DM(policy): adjustment FEED-IN tariff with support index	Electricity generation costs	2002	2009	South Korea	0.98	43%				Support index (SI) to adjust electricity price with FEED-IN tariff
[135]	LBR: Cumulative capacity shipped. LBR: Knowledge stock (RD&D expenditures)	Module prices	1975	2000	Global	0.99	18,40%	14%			

[142]	LBD: Cumulative capacity installed. LBR: Knowledge stock (RD&D expenditures)	Investment costs	1971	1998	Global	0.94	17,50%	10%			
[133]	ES: manufacture plant size	Module costs	2005	2012	Global	0.64	n.s.s.		1.54		
[133]	LBD: Cumulative capacity produced (global industry). LBR: annual module firm efficiency, silicon usage. ES: manufacture plant size. IM: Silicon price. DM: industry annual investments, Chinese production dummy	Module costs	2005	2012	Global	0.93	n.s.s.	Silicon usage: -42% Annual Module efficiency: 45%	n.s.s.	-70%	annual industry investments =17%
[133]	LBR: annual module firm efficiency, Silicon usage. IM-S: Silicon price. DM (competitors): industry annual investment, Chinese production dummy. IM-S: single firm annual investment (capital costs).	Module costs	2005	2012	Global	0.93		Silicon usage: -42% Annual Module efficiency: 47%		Silicon price: -89% annual firm investme nts : n.s.s.	annual industry investment =17%
[133]	LBR: annual module firm efficiency, Silicon usage. IM-S: Silicon price. DM (competitors): industry annual investment, cumulative industry investments, Chinese production dummy.	Module costs	2005	2012	Global	0.92		Silicon usage: -46% Annual Module efficiency: 52%		Silicon price: -96%	Cumulative Industry investment: n.s.s. , annual industry investments :20%

[133]	LBR: annual module firm efficiency, silicon usage. ES: manufacture plant size. IM-S: Silicon price. DM (competitors): industry annual investments, Chinese production dummy	Module costs	2005	2012	Global	0.92		Silicon usage: -43% Annual Module efficiency: 50%		Silicon price: -88%	annual industry investments :16%
[158]	LBD: Cumulative capacity installed. Interference variables: steel price, oil price, silicon price	Investment costs	2001	2014	Taiwan	0.975	12%			1%	Oil price: n.s.s.
[143]	LBD: Cumulative capacity installed. LBR: Public R&D expenses	Module prices	1992	2012	Global	0.821	10%	n.s.s.			
[23]	LBD: Cumulative capacity installed. IM-S: Silicon index, Silver index, other input price. ES: manufacture plant size	Module prices	1976	2006	China	n/a	14%		1.07	Silicon: -21.80% Silver: 9% Other materials: -80%	
[138]	LBD: Cumulative capacity installed. IM-S: Silicon prices	Module prices	1988	1996	Global	0.93	9.30%			Not available	
[138]	LBD: Cumulative capacity installed. IM-S: Silicon prices	Module prices	1997	2001	Global	0.68	8.20%			Not available	
[138]	LBD: Cumulative capacity installed. IM: Silicon prices	Module prices	2002	2006	Global	0.68	7.70%			Not available	

[138]	LBD: Cumulative capacity installed. IM-S: Silicon prices	Module prices	1997	2002	Global	0.91	5.20%			Not available	
[138]	LBD: Cumulative capacity installed. IM: Silicon prices. DM: Supply-demand imbalance.	Module prices	2002	2006	Global	0.90	5.70%			Not available	Not available
[138]	LBD: Cumulative capacity installed. IM: Silicon prices. DM: Chinese module share on global production	Module prices	1988	2006	Global	0.90	5.90%			Not available	Not available
[145]	LBD: Cumulative capacity installed. LBR: Public R&D	Investment costs	2009	2016	US	0.949	11%	66%			

Notes:

a) In knowledge spillovers (KS) and demand market (DM) column only the significant results are reported. If no results is reported for a MFLC that includes these drivers it means that the results are not statistically significant

b) Economies of scale results are referred to return to scale parameter.

c) Results for dummy variables parameters are not reported.

d) “Investment costs” covers all the cost variables expressed per kW units. Variables as “installation costs”, “turn-key costs”, “module prices”. Studies provide limited information about their cost elements and definitions about what is taken into account in their cost variables. There is not distinction between cost and price variables.

e) “Electricity generation cost” refers to “LCOE” and “electricity prices”. There is not distinction between cost and price variables.

f) Geographical domain is referred to the cost variable in the MFLCs

g) Knowledge stock refers to the annual RD&D expenditures taking into account the depreciation of knowledge and the time-lag from between funded year and implementation.

For each regression model developed in the literature review papers different statistical tests are run in order to develop a significant analysis with the dataset available. Each paper shows its descriptive statistic tables together with the results, here we reported only the result of the coefficient of determination (R^2) found for each learning curve, more information is available in the papers.

Appendix B

This appendix serves to provide assumptions on data and methodology used in Chapter 3.

B. 1 Material prices data

Here as follow the data related material prices assumptions are reported in Table B-1. Figure B-1 reports the trend in the time-period of the analysis. Data on copper, aluminium prices are based on world bank annual pink sheets [258]. Steel prices are based on hot-rolled steel sheet price index from FRED database and annual average price from US geographical surveys [44, 259]. Iron price is based on cast iron material, data are taken from FRED database [44] and compared with multi-resources. Cement price is based on Statista database [260]. Polymers and composites price indexes are taken from [44] and current values are based from online sources. Datasets on polymers include polyethylene high density granulate (PEHD), ethylene propylene diene elastomer (EPDE), or polyvinylchloride (PVC). Data on composites are based on epoxy resin and Glass fibres. We did not include in the analysis lubricant and electronics materials because of the limited cost data availability for these materials, these are a minimal part of the material required for the turbines, thus most probably total material costs for each turbine are slightly higher if these material would be considered.

Table B-1. Materials' prices assumptions

[$2016/ton]	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Copper	5001	8900	9194	8663	4054	9177	10460	9227	8362	7697	6140	5366	6651
Aluminium	2581	3438	3407	3205	1702	2647	2845	2345	2105	2094	1855	1768	2121
Cast Iron	711	765	807	984	989	1028	1102	1163	1151	1153	1159	1170	1135
Steel hot-rolled steel sheet	691	694	706	828	740	730	764	751	722	710	666	624	618
Cement prices	141	138	134	129	123	112	106	104	108	113	119	122	122
Glass fibres - Epoxy resin	812	814	797	812	856	845	872	856	1004	1020	1010	1000	978
Polymer	1703	1732	1754	1840	1911	1881	1934	1982	2004	1958	1948	1906	1928

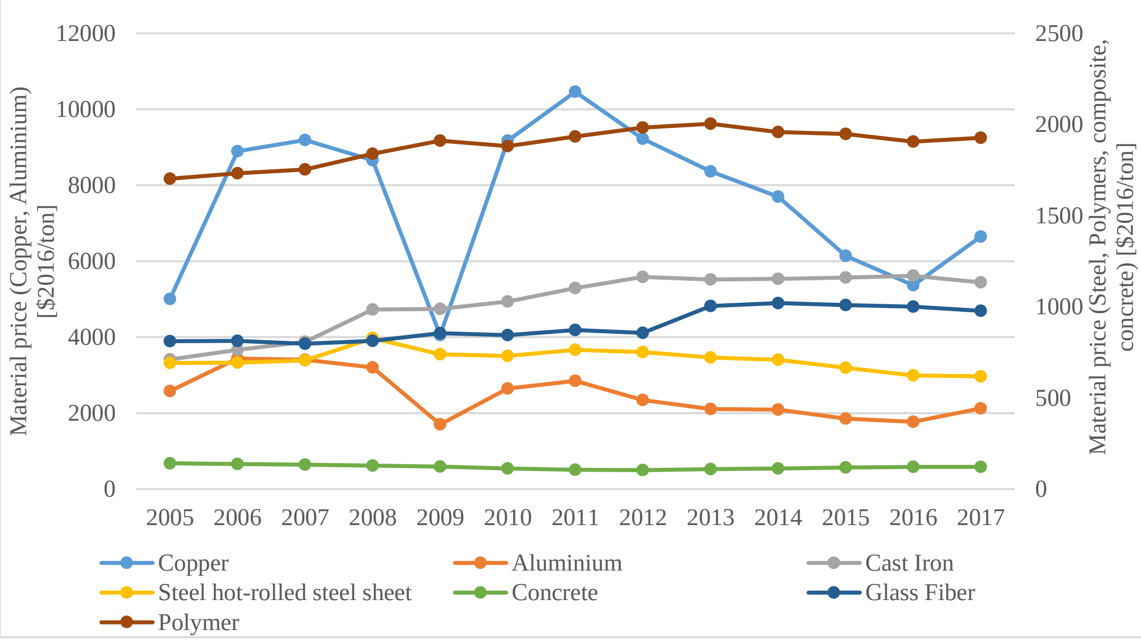


Figure B-1. Materials' price trend

B. 2 Material dataset

To evaluate the material quantity data are taken from [169]. Vestas provides the amount of materials used for each turbine type analysed in the LCA reports (Table B-2). The material breakdown regards material used for building turbines, foundation, site cables, site switchgears and site transformer. Thus, the materials used to build all the device components part of nacelle as alternator, gearbox, power electronics (see [186]) are not provide. This is because these components are usually produced by external specialized suppliers, this allows specific innovation in the production of these equipment.

B. 3 Annual Turbines' Type Assumptions

Material characteristics per turbine type are reported in Table B-2, data provided by VESTAS LCA reports [169, 261].

Table B-0-3 presents the amount of turbines installed for each turbine type, the main installed turbine for each year is used as reference, the turbines chosen for each year are highlighted in green.

The data for

Table B-0-3 are taken from Make consulting which provides the amount of MW grid connected each year for each type of turbine. Knowing the size of the turbine we calculated the amount of turbine installed for each type for each year. It can be observed that even if rotor and height size adopted are increasing, the main average turbine nameplate installed is 2 MW. Between bigger size model, V90 3MW and V112 3MW have been a discrete successful in deployment, but probably technology scale problems to adapt to delivery equipment, material quantity and risk of curtailment in most of the countries still force to prefer 2 MW turbines onshore varying mainly the blade size only.

Table B-2. Turbines characteristics. Material amount used for each turbine type is in [ton/turbine] (it includes foundations weight)

Model	**v82-1.65 MW**	**V90-2MW**	**v80 - 2MW**	**v100 - 1.8MW**	**v112-3MW**	**v90-3MW**	**v100-2.6 MW**	**v105-3.3 MW**	**v117-3.3 MW**	**v126-3.3 MW**	**v100-2 MW**	**v110-2 MW**	**v112-3.3 MW**	**v105-3.45 MW**	**v112-3.45 MW**	**v117-3.45 MW**	**v126-3.45 MW**	**v136-3.45 MW**	**v120 - 2 MW**	**v116-2MW**
Year	2005	2009	2009	2009	2009	2011	2011	2012	2012	2012	2013	2013	2013	2015	2015	2015	2015	2015	2017	2017
Capacity [MW]	1.65	2	2	1.80	3	3	2.60	3.3	3.3	3.3	2	2	3.3	3.45	3.45	3.45	3.45	3.45	2	2
Rotor [m]	82	90	80	100	112	90	100	105	117	126	100	110	112	105	112	117	126	136	120	116
Height [m]	78	80	80	80	84	90	80	72.5	91.5	117	80	80	84	72.5	94	91.5	117	132	118	80
Steel	180	206	255	206	290	248	247	302	348	459	214	261	272	304	403	399	495	577	297	208
Iron	29	40	40	41	66	33	33	64	64	64	27	27	64	70	70	70	72	72	37	37
Aluminium	9	26	26	24	3	10	9	9	10	10	11	10	9	9	9	10	11	12	9	9
Copper	5	7	7	6	5	6	7	4	4	4	4	3	4	5	5	5	5	5	4	4
Polymers	12	51	49	45	22	15	13	31	31	32	23	27	30	30	30	31	32	35	23	22
Concrete	805	751	1105	758	902	987	986	976	1140	1334	803	913	809	1032	1395	1395	1368	1861	912	733
Composites	27	21	19	22	27	12	18	32	32	28	22	16	31	26	26	29	26	25	20	20
Electronics	3	2	2	2	2	2	2	3	3	4	2	2	4	3	3	3	3	4	3	3
Lubricant	2	2	2	2	1	2	2	2	2	2	2	1	2	2	2	2	2	2	2	2

Table B-0-3. Number of turbine installed (global data)

Year	v82 – 1.65 MW	V90-2MW	v80 - 2MW	v100 - 1.8MW	v112 - 3MW	v90-3MW	v100-2.6 MW	v105-3.3 MW	v117-3.3 MW	v126-3.3 MW	v100-2 MW	v110-2 MW	v112-3.3 MW	v105-3.45 MW	v112-3.45 MW	v117-3.45 MW	v126-3.45 MW	v136-3.45 MW	v120-2 MW	v116-2MW
2005	223	138	294			57														
2006	179	300	401			128														
2007	424	461	267			214														
2008	383	408	159			407														
2009	839	767	114	1		416														
2010	89	656	186	1	2	409														
2011	143	719	45	206	63	485	1				15									
2012	176	1049	187	655	340	335	51				45		1							
2013	11	639	104	222	407	242	34		5	3	142		31							
2014	11	331	22	356	536	141			9	15	573	109	141							
2015	0	348	68	34	365	67			30	178	1379	440	352		13	1	1			
2016	0	112	45	22	54	70			380	315	807	1193	353		32	75	60	2		
2017	0	50		12	22	52			98	146	442	1208	196	9	64	245	324	50		1

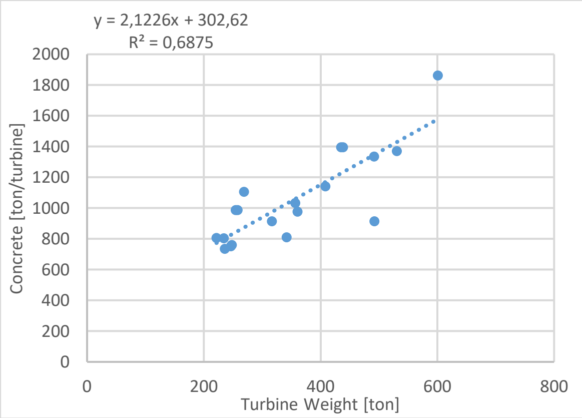
B.4 Economies of scale between turbine size and materials

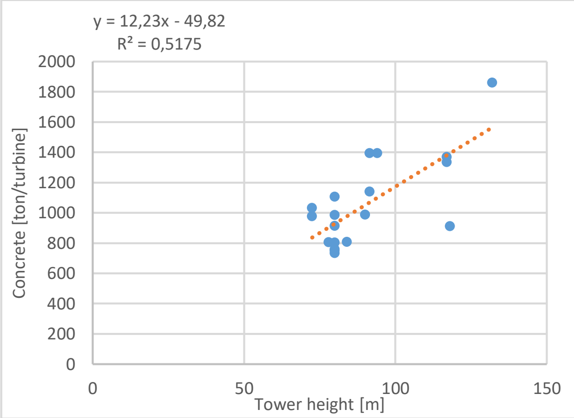
In this section the results from the economies of scale analysis are reported.

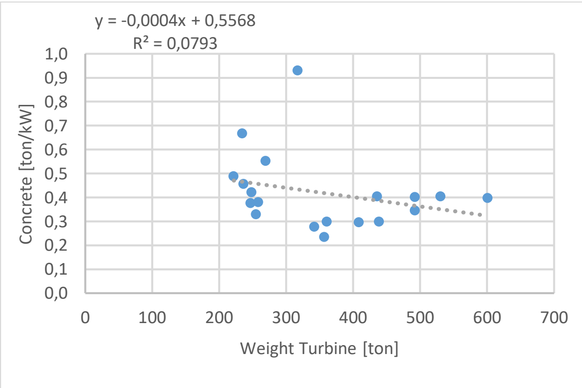
The first analysis done compares turbine material use according to different technical features of turbine as nameplate size, rotor length, tower height, and turbine weight. In Table B-4 the correlation results between the variables analysed are reported. Through the correlation analysis between materials amount used per turbine and turbine characteristic the following results are found: steel and concrete ton per turbine show high grade of correlation with tower height and turbine weight; lower correlation grade between glass fibres used per turbine with the all the variables investigated. If the analysis is compared with amount of material per kW of turbine the low grade of correlation is found for most of the variables beside steel amount per kW with tower weight (see table below).

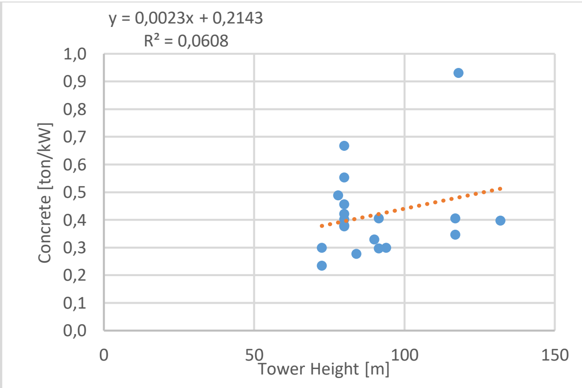
Table B-4. Correlation between variables analysis

	Test variable: unit of material per turbine [ton/turbine]	**Test variable: unit of material per kW [ton/kW]**
GLASS FIBRES CORRELATION		
Rotor length [m]	0.365	-0.35
Weight [ton]	0.34	-0.45
Nameplate size [MW]	0.53	-0.62
STEEL CORRELATION		
Tower height [m]	0.83	0.8
Weight [ton]	0.91	0.6
Nameplate size [MW]	0.72	-0.05
CONCRETE CORRELATION		
Tower height [m]	0.72	0.24
Weight [ton]	0.83	-0.28
Nameplate size [MW]	0.69	-0.6









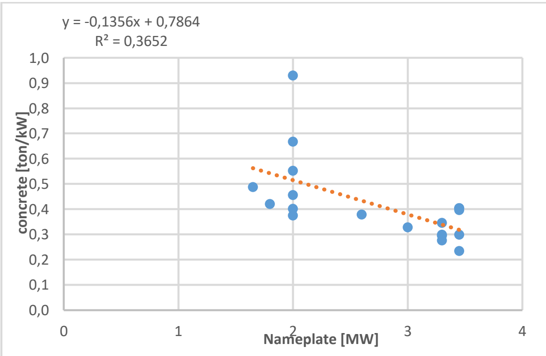
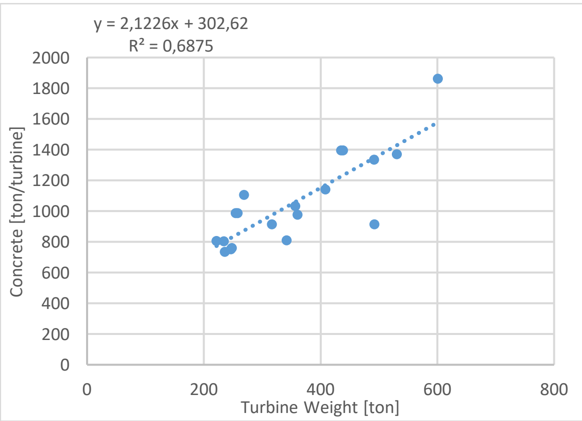
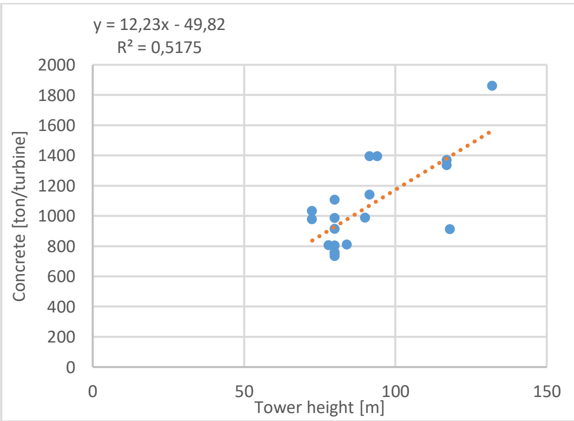
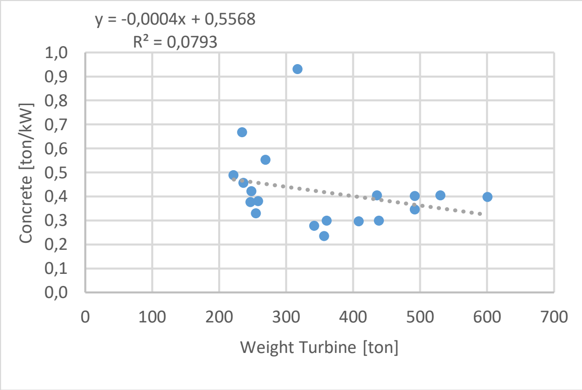
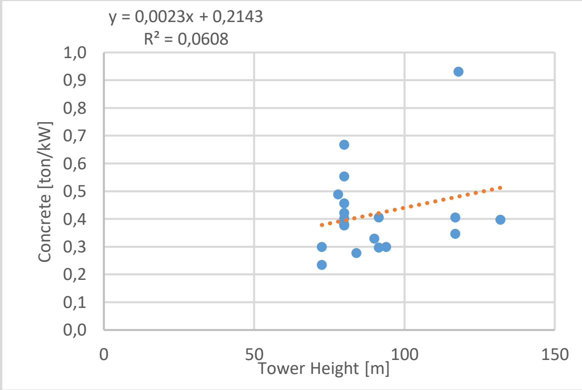


Figure B-2, Figure B-3 and show the linear correlation between steel or concrete quantity and technical turbine characteristics, the fit coefficients and goodness of fit are presented.









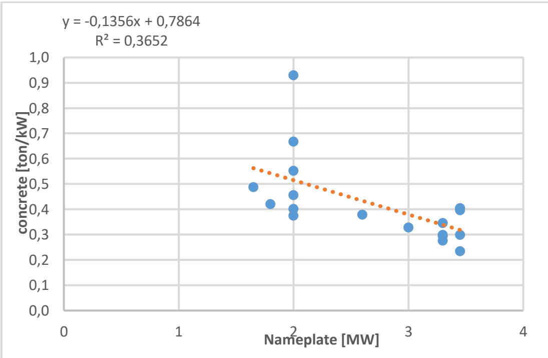
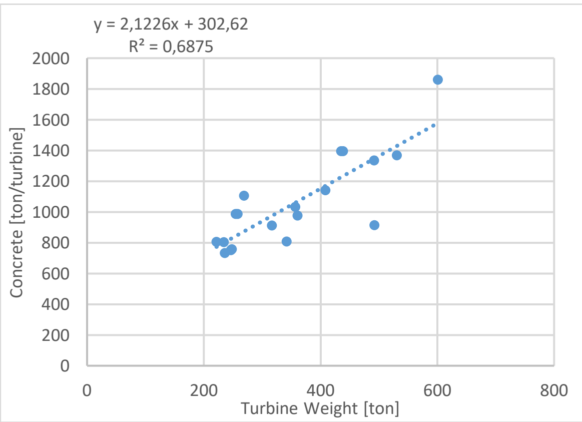
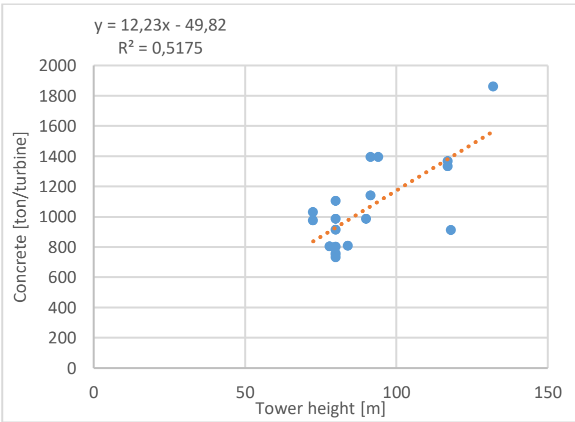


Figure B-2 shows that the concrete quantity [ton/kW] decreases with the adoption of bigger nameplate size, thus there are economies of scale. As expected higher tower and weightier turbines use more concrete per turbine, while if we compare the amount of concrete used per unit of power produced with turbine weight the amount used decreased. This means that turbines doubling weight more than double the nameplate, thus the amount of concrete used per unit of power is less. Mixed proportionality is found between tower height and concrete per kW.





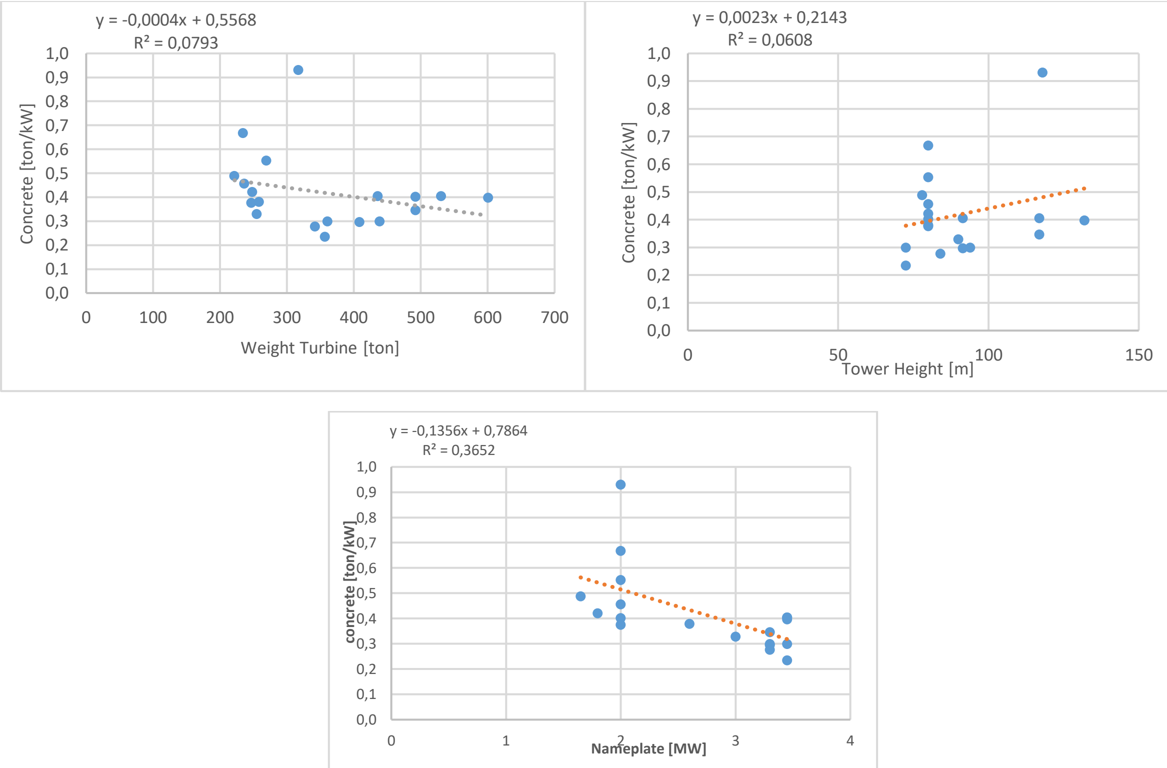
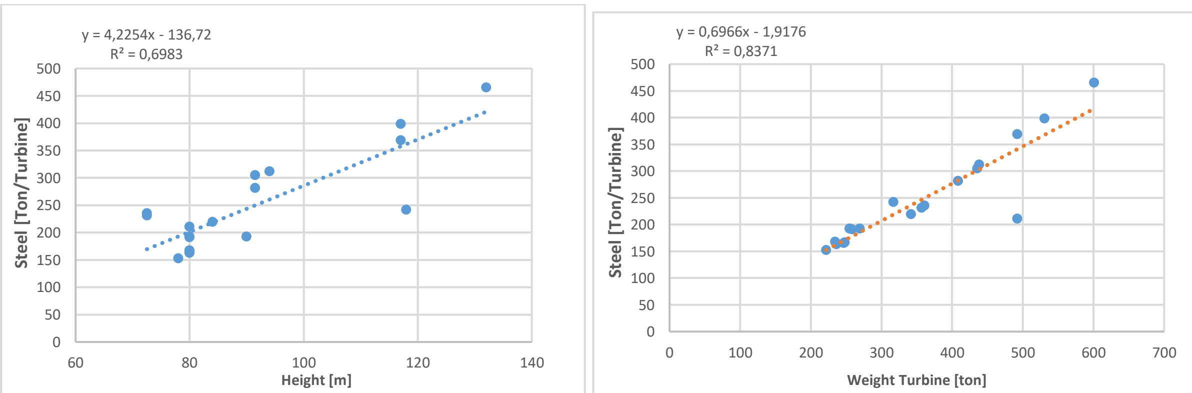


Figure B-2. Correlation between concrete material amount and wind turbine technical parameters

In Figure B-3 it is observed steel quantity per turbine [ton/tubine] increases if tower height and turbine weight increase. The results comparing steel quantity per unit of power produced with height and weight show mixed results. For low tower height the results are mixed, for taller turbines the use of steel per unit of power produced increase. Similarly occurs between steel per power produced [ton/kW] and turbine weight. With the increase of the nameplate the steel used per unit of power [ton/kW] decreases till 3 MW and then it tends to increase again.



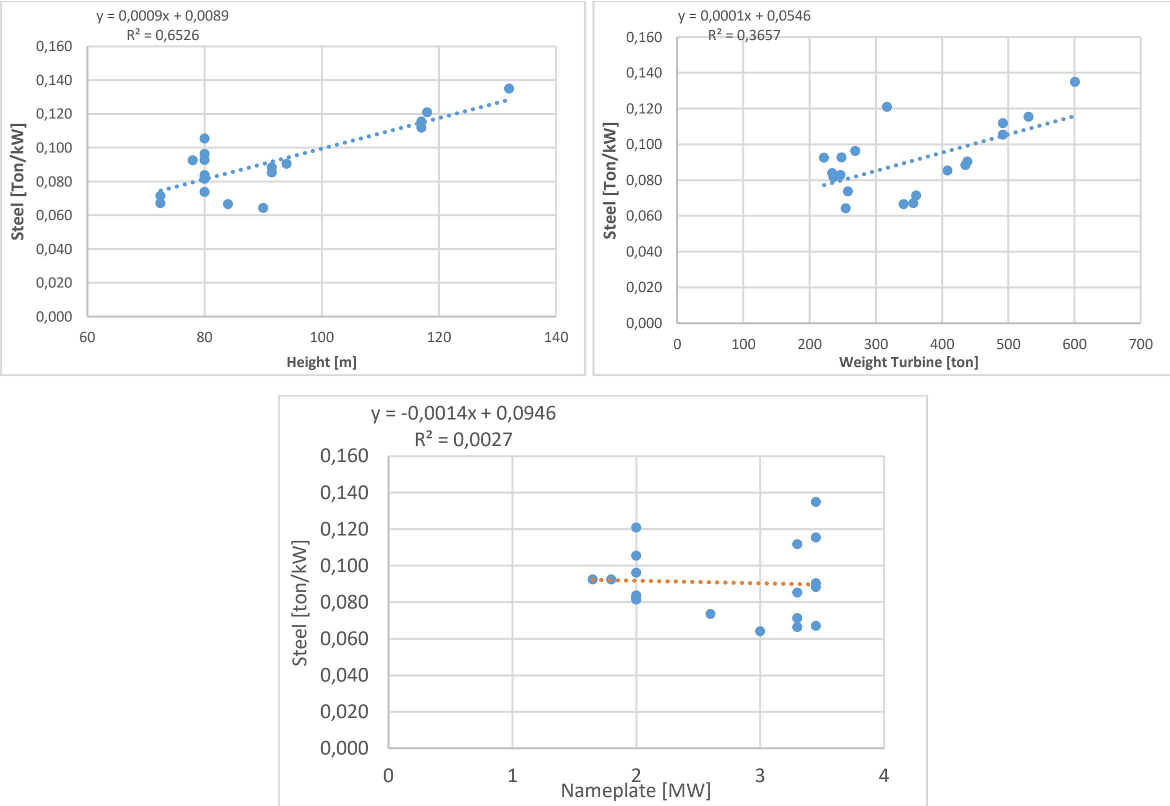


Figure B-3. Steel quantity correlation with turbine technical parameters

The previous figures show that steel quantity may present some diseconomies of scale, particularly for the adoption of bigger turbines (>3 MW). We investigated economies of scale for three different size of nameplate: 1.65 MW, 2 MW, and 3.45 MW. The database of turbines available presents more type of turbines for the type of nameplate size compared, for this reason average value of rotor length, tower height, weight of turbine and material amount is adopted for each nameplate size (Table B-5). These results provide insights based on average values, a bigger sample size of turbines will provide better statistics.

The equation adopted is based on [43]. In this case, economies of scale exist when the percent increase in material used (ton/turbine), is lower than the percent increase in turbine size being investigated as nameplate size (kW). The following equation shows the mathematical expression used to evaluate the material-size elasticity E_{mq}, where *m* represents the material used [ton/turbines] and *q* the parameter used to measure the scale, in this case the nameplate size [MW]. The material-size elasticity results are presented in Table B-6, steel presents negative economies of scale (elasticity >1) with the nameplate increase both between 1.65 to 2 MW and 2 MW and 3.45 MW. The other two materials investigated show positive economies of scale.

$$E_{mq} = \frac{\frac{\Delta m}{m}}{\frac{\Delta q}{q}} < 1 \tag{A1}$$

Table B-5. Average values of variables used to evaluate material-size elasticity as in Equation A1

Average values in the turbine size range	**1.65 MW**	**2 MW**	**3.45 MW**
Fiberglass [ton/turbine]	27	19.5	26
Steel [ton/turbine]	152	190	342
Concrete [ton/turbine]	805	886	1410
Nameplate size [MW]	1.65	2	3.45
Length rotor - blades [m]	45.5	51	59.6
Height [m]	79	85	101
Weight [ton]	235	293	472

Table B-6. Result economies of scale

	Material-size elasticity (1.65 – 2 MW)	**Material-size elasticity (1.65 – 3.45 MW)**	
Glass Fibres- nameplate	-1.31	-0.02	Positive Economies of scale
Steel- nameplate	1.19	1.15	Negative economies of scale
Concrete-nameplate	0.48	0.69	Positive Economies of scale

B.5 Energy costs

First, annual primary energy consumption (PEC) are collected from the financial reports of Vestas [170]. Primary energy is reported as total consumption, renewable consumption and only electricity renewable consumption. From LCA reports from Vestas the disaggregation about the type of energy resource is provided. The assumption about the percentage of resource used it is based on the annual LCA reports, not all the reports provides this disaggregation in energy resource, thus only the values from the years available are used and an average value is assumed. Table B-7 shows the primary energy consumed and the division by energy resources adopted. We agree this is an assumption, which not takes into account the variation of energy type in each primary energy consumption category but the impact of energy cost on turbine is minimal, and this assumption will not interfere with the results. **Errore. L'origine riferimento non è stata trovata.** shows the consumption of primary energy resources by fuel according to the turbine total annual amount delivered by Vestas.

Table B-7. Electricity consumption by type and by fuel

[GWh]	Total PEC	Not RES	RES	RES-E	Oil	Natural Gas	Coal	Uranium	Wind	Hydro	biomass
2005	228	110	118	118	44.0	35.2	22.0	8.8	88.5	29.5	0.0
2006	330	205	125	125	82.0	65.6	41.0	16.4	93.8	31.3	0.0
2007	372	232	140	138	92.8	74.2	46.4	18.6	103.5	34.5	2.0
2008	458	286	172	167	114.4	91.5	57.2	22.9	125.3	41.8	5.0
2009	537	273	264	238	109.2	87.4	54.6	21.8	178.5	59.5	26.0
2010	578	336	242	209	134.4	107.5	67.2	26.9	156.8	52.3	33.0
2011	586	363	223	208	145.2	116.2	72.6	29.0	156.0	52.0	15.0
2012	630	303	327	310	121.2	97.0	60.6	24.2	232.5	77.5	17.0
2013	586	261	325	309	104.4	83.5	52.2	20.9	231.8	77.3	16.0
2014	501	223	278	255	89.2	71.4	44.6	17.8	191.3	63.8	23.0
2015	516	233	283	257	93.2	74.6	46.6	18.6	192.8	64.3	26.0
2016	567	271	296	268	108.4	86.7	54.2	21.7	201.0	67.0	28.0
2017	569	244	325	264	97.6	78.1	48.8	19.5	198.0	66.0	61.0

* RES: Renewable Energy Resources. RES-e: Renewable energy resources electricity

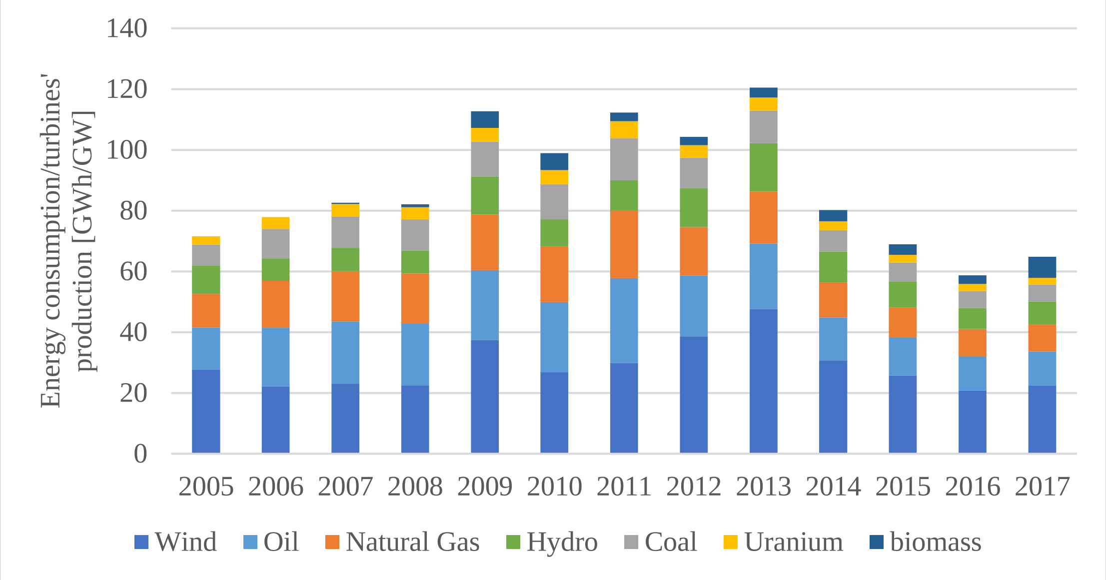


Figure B-4 Annual primary energy consumed per 1 GW of turbine produced (data from Vestas financial reports [170])

To evaluate the cost of energy, we considered as the company buys thermal energy for the processes and electricity from external sources. Assumption about the contribution of natural gas to thermal energy production or electricity are based on statistics from [181], in this report the share of global electricity generation by fuel is provided. We assumed that the share of electricity from natural gas is equal to the 60% of electricity produced with coal, the rest is used for thermal energy. Thus 37.5% of the natural gas primary energy consumption is used to provide electricity, 62.5% for thermal energy. Thermal energy is produced with oil, natural gas, and biomass, while electricity is produced from wind, solar, uranium and natural gas (Table B-8).

Table B-8. Energy resources divided by electricity provided and thermal energy provided

[GWh]	**Oil**	**Natural Gas**		**Coal**	**Uranium**	**Wind**	**Hydro**	**biomass**	**Total**	
Use	Thermal	Electricity	Thermal	Electricity	Electricity	Electricity	Electricity	Thermal	Electricity	Thermal
2005	44	13.2	22	22	8.8	88.5	29.5	0	162	66
2006	82	24.6	41	41	16.4	93.8	31.3	0	207	123
2007	92.8	27.84	46.4	46.4	18.6	103.5	34.5	2	231	141
2008	114.4	34.32	57.2	57.2	22.9	125.3	41.8	5	281	177
2009	109.2	32.76	54.6	54.6	21.8	178.5	59.5	26	347	190
2010	134.4	40.32	67.2	67.2	26.9	156.8	52.3	33	343	235
2011	145.2	43.56	72.6	72.6	29	156	52	15	353	233
2012	121.2	36.36	60.6	60.6	24.2	232.5	77.5	17	431	199
2013	104.4	31.32	52.2	52.2	20.9	231.8	77.3	16	413	173
2014	89.2	26.76	44.6	44.6	17.8	191.3	63.8	23	344	157
2015	93.2	27.96	46.6	46.6	18.6	192.8	64.3	26	350	166
2016	108.4	32.52	54.2	54.2	21.7	201	67	28	376	191
2017	97.6	29.28	48.8	48.8	19.5	198	66	61	362	207

We assumed the production of turbine is occurring in the same place where the final turbine is installed, thus energy required for transportation is not included in this analysis, manufacturing stage is defined as the most significant component in the life-cycle assessment analysis done by Vestas [201].

Electricity prices are based on OECD average electricity price for industries provided by Eurostat statistics [262]. Thermal energy prices for fossil fuels as oil and natural gas are based on BP statistics report [181], this values are provided by regions, oil thermal energy prices are based on OECD region while natural gas is disaggregated by three macro regions: Americas, Europe-Africa and Asian countries. Biomass thermal energy is based on internal data provided by IRENA [182], and it is assumed no variation in the time period considered from the analysis if not because of the inflation. The values assumed about the prices are reported in Table B-9. The values do not account for any carbon tax.

Table B-9. Electricity and thermal energy price assumed

	Average electricity price by industry [$2016/kWh]	**Biomass thermal energy price [$2016/kWh]**	**Natural Gas thermal energy price [$2016/kWh]**			**Crude oil thermal energy price [$2016/kWh]**
	OECD	OECD	Asia	Europe	America	OECD
2005	0.147	0.0221	0.03	0.032	0.04	0.044
2006	0.138	0.0216	0.035	0.038	0.031	0.052
2007	0.147	0.021	0.037	0.032	0.031	0.057
2008	0.167	0.0203	0.058	0.05	0.039	0.077
2009	0.161	0.0202	0.033	0.028	0.016	0.048
2010	0.148	0.0198	0.042	0.032	0.018	0.06
2011	0.163	0.0193	0.063	0.0422	0.016	0.081
2012	0.15	0.01892	0.0686	0.0428	0.010	0.081
2013	0.16	0.0186	0.069	0.044	0.014	0.077
2014	0.157	0.0183	0.063	0.0356	0.017	0.07
2015	0.13	0.018	0.0367	0.027	0.0095	0.036
2016	0.118	0.018	0.0259	0.012	0.0082	0.028
2017	0.115	0.0176	0.03	0.023	0.00913	0.0359

This values are multiplied with the values in Table B-8 and divided by the capacity delivered annually by Vestas, taking into account that natural gas has been disaggregated into the three regions proportionally to the turbine installed in that regions (Table B-10). Data on turbine installed are based on Vestas financial reports and Make consulting database [180].

Table B-10. Natural gas disaggregation baed on the location where turbines are installed according to Vestas financial reports, and Vestas annual delivery of turbines

	Natural Gas [GWh]			**Delivered capacity by year**
	Africa- Europe	America	Asia	GW
2005	11.5	5.6	5.0	3.185
2006	22.5	8.0	10.4	4.239
2007	22.6	11.7	12.1	4.502
2008	25.7	17.5	13.9	5.58
2009	25.2	20.3	9.1	4.764
2010	36.7	8.9	21.6	5.842
2011	32.5	30.0	10.1	5.217
2012	30.2	22.2	8.2	6.039
2013	30.8	8.7	12.6	4.862
2014	27.6	12.7	4.3	6.252
2015	21.6	21.5	2.8	7.486
2016	23.3	26.6	4.3	9.654
2017	22.5	21.7	4.7	8.779

B.6 Labour cost

From [170] it is possible to gather data on annual staff costs and number of employees. In this analysis the total staff costs are taken into account, the different company department labour costs are not disaggregated due to the missing of reliable data for each category in each year of the analysis, and differences in accounting found in the annual reports.

The two techno-economic variables salary and employees' productivity are evaluated starting from these two variables, the values obtained are reported in Table B-11.

Table B-11. Techno-economic variables and initial data assumptions for labour cost components

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Salary [M€/EN]	0.0443	0.0451	0.0442	0.0438	0.0466	0.0441	0.0535	0.0718	0.0672	0.0607	0.0630	0.0657	0.0626
Employees' productivity [EN/kW delivered]	0.0033	0.0029	0.0034	0.0037	0.0044	0.0040	0.0044	0.0029	0.0031	0.0028	0.0027	0.0023	0.0027
Staff cost [M€]	470.2	555.6	676	912	967	1025	1215	1276	1021	1068	1292	1433	1458
Employees number (EN)	10618	12309	15305	20829	20730	23252	22721	17778	15192	17598	20507	21824	23303

B.7 Depreciation costs assumptions

Vestas financial reports [170] provide the value of depreciation capital, but the dataset available does not allow to separate the cost of equipment from their interest cost, and quality of machine impact. Thus, the general depreciation of capital costs is used a proxy parameter used to represent the whole impact of capital cost. The data used are available in Table B-13.

B.8 Delivery cost: distribution and installation costs

The data assumption used for distribution costs are presented in Table B-13 based on Vestas financial reports [170]. Installation costs are based on NREL reports [168]. This document report the percentage of impact of this cost component on total costs per year (Table B--14). The cost component based on this data do not allow to include a specific techno-economic variable analysis because they are evaluated as a percentage of the overall annual average turbine prices.

B.9 R&D, financial and legal costs

As for installation costs also financial and legal costs are based on NREL reports [168], and data reported in Table B--14. Given the lack of detail in the financial reports the assumption from NREL reports are used to allow to separate these cost components from the residual cost components. NREL reports provides the share of impact on wind turbine prices.

Assumption on R&D costs are based on Vestas reports [170] and reported in Table B-13. Due to variation of annual accounting of this cost component is not possible to separate R&D costs from cost of labour or capital depreciation related to the R&D Vestas department, better assumption would help to further disaggregate this cost component, which otherwise may have some double counting with the other cost components.

B.10 Company profit

Data used to for company profit are in Table B-13. They are based on 8% of Vestas total asset.

B.11 Suppliers & Others

This cost is evaluated as the total of annual average wind turbine prices less all the other cost components. The values are reported in Table B-12.

B.12 Data assumption: exchange rate and inflation rate

All the cost components are presented in unit of $ inflated 2016 per kW delivered. The data used for these assumptions are reported in Table B-12. Exchange rate are based on average annual values from OECD database (available at https://data.oecd.org/). Inflation values are based on Consumer Price Index (CPI), assuming the annual average for OECD countries (available at https://data.oecd.org/). Values of capacity delivered and order in-take are based on Vestas reports [170]. Material costs are evaluated on the turbine name plate, labour, profit, energy costs, distribution costs and capital depreciation costs are on delivery capacity by year of Vestas.

Table B-12. Other data used in this analysis

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
CPI inflation OECD	81	83	85	89	89	90	93	95	97	98	99	100	102
Exchange rate [EUR/$]	0.804	0.797	0.731	0.683	0.72	0.755	0.719	0.778	0.753	0.754	0.902	0.904	0.887
Delivered capacity by year [GW]	8.779	9.654	7.486	6.252	4.862	6.039	5.217	5.842	4.764	5.58	4.502	4.239	3.185
Order in-take capacity by year [GW]	11.176	10.494	8.943	6.544	5.964	3.738	7.397	8.673	3.072	6.019	5.613	5.175	

Table B-13 Cost components data assumptions

[$2016/kW]	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Labour costs	226	198	241	270	317	257	348	286	289	231	193	164	183
Capital costs (Capital Depreciation)	59	44	49	40	72	94	105	223	114	81	46	46	54
Energy costs	8	8	9	11	13	11	14	13	16	10	7	5	5
Profit (total asset - 8%)	119	104	151	150	209	142	176	125	128	121	103	91	109
Materials (Turbine)	182	208	205	217	177	205	218	209	202	135	127	135	138
Materials (foundations)	87	85	64	64	60	56	54	53	55	61	63	71	71
Material (Steel)	76	77	73	85	76	75	79	77	74	76	71	81	81
Material (concrete)	78	76	50	48	46	42	40	39	41	45	48	56	56
Material (Fiberglass)	8	8	8	9	9	9	9	9	11	11	11	8	8
Material (others)	107	133	138	139	106	135	145	137	131	64	60	61	65
Distribution turbine costs	19	25	35	54	58	52	60	46	55	34	28	22	29
Installation costs	67	67	76	87	79	73	92	97	114	60	55	61	56
Legal and Financial costs	121	121	138	156	143	132	138	124	114	108	92	96	90
Suppliers & Others	416	455	537	618	378	354	213	158	114	326	305	273	162
RD&D costs	42	31	24	67	82	93	115	49	68	28	20	23	28
Annual average turbine prices (Vestas)	1348	1347	1529	1734	1588	1469	1534	1383	1267	1195	1039	987	925

Table B--14. Cost component percentage of wind turbine price based on NREL database

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Assembly and installation & site accessing and staging	5%	5%	5%	5%	5%	5%	6%	7%	9%	5%	5.3%	6.2%	6.1%
Legal and financial costs	9%	9%	9%	9%	9%	9%	9%	9%	9%	9%	8.9%	9.7%	9.7%

B.13 Methods applied: Techno-economic variables contribution: finite differential method

Here following the explanation about the method approach used to identify the contribution of techno-economic variables on each cost component.

Taking a function of two variables $f(x, y) = xy$, incrementing both the variables of the function of a delta we can write:

$$f(x + \Delta x, y + \Delta y) = (x + \Delta x)(y + \Delta y) = xy + x\Delta y + y\Delta x + \Delta x\Delta y = f(x, y) + \Delta f \qquad \text{(B.1)}$$

The decomposition for finite difference is written as in the following expression

$$\Delta f = x\Delta y + y\Delta x + \Delta x\Delta y = \Delta y\left(x + \frac{1}{2}\Delta x\right) + \Delta x\left(y + \frac{1}{2}\Delta y\right) = \Delta f_y + \Delta f_x \qquad \text{(B.2)}$$

Where the first term of Eq. B.2 can be considered as the variation of *f(x, y)* due to the change in y and the second term as the variation of *f(x, y)* due to the change in x.

We assumed that each cost component variation Δf is the sum of the contribution related to each variable variation *x,y*. The single variable contribution may be evaluated as in Eq. B.1, Eq. B.2. This analysis has been implemented by using Microsoft excel software, excel sheets are developed from scratch for this analysis without using a pre-defined toolbox or library.

B.14 Drivers result graphs including cost components

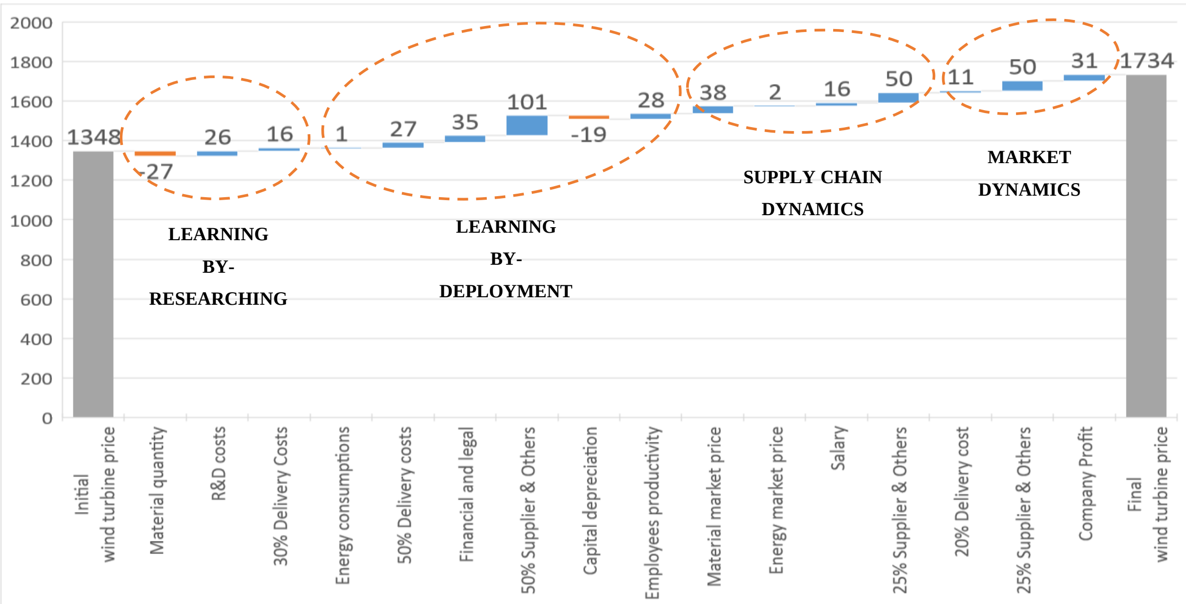


Figure B-5. Cost changes contribution of drivers divided by the different cost components contribution as in Table 3-4 in the time period between 2005 and 2008. Values in \$2016/kW.

Comparing with the whole period (Figure 3-12 in Chapter 3) with the results in **Errore. L'origine riferimento non è stata trovata.**, the role of market dynamics and supply-chain dynamics is higher, while learning by-researching is minimal and learning by-deployment is still dominant but below 50%. The barriers encountered during this period justify a higher role of supply-chain and market dynamics.

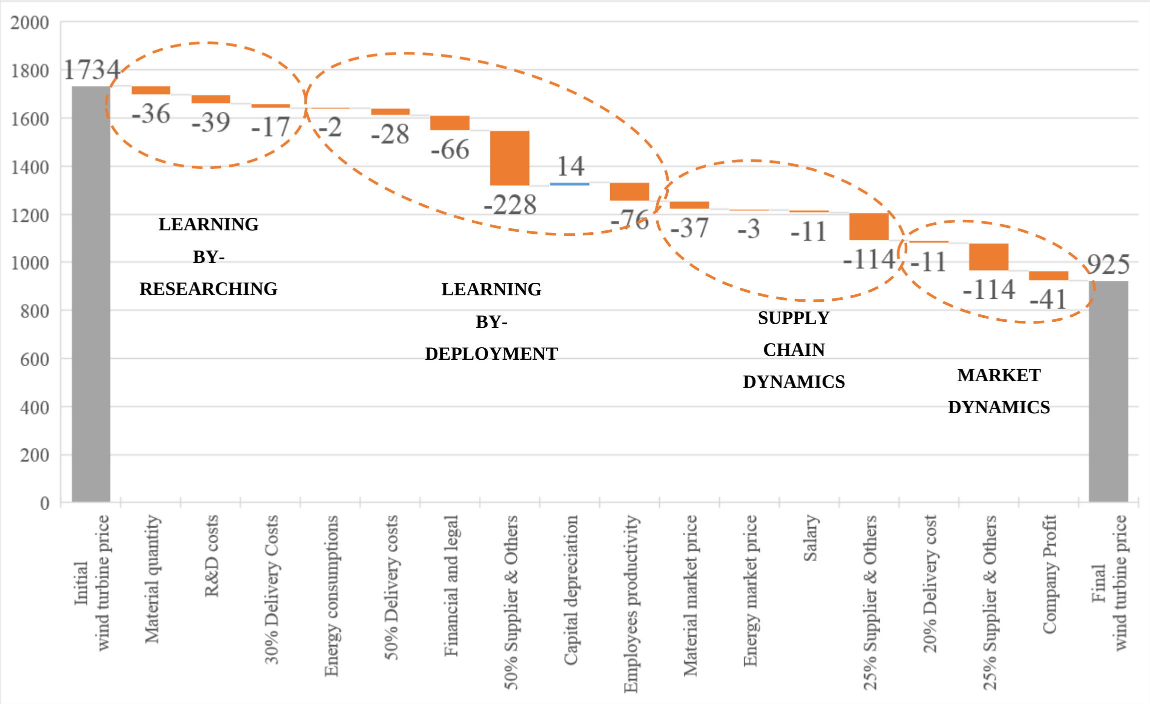


Figure B-6. Cost changes contribution of drivers divided by the different cost components contribution as in Table 3-4 in the time period between 2008 and 2017. Values in $2016/kW

Comparing with the whole period ((Figure 3-12 in Chapter 3) with the results in **Errore. L'origine riferimento non è stata trovata.**, the role of market dynamics and supply-chain dynamics is higher, while learning by-researching is reduced by sharing 11% of cost reduction impact. Learning by-deployment is still dominant but below 50%.

B.15 Sensitivity analysis of drivers' categories

In the main text a base case assignment of drivers for each cost or techno-economic variable is proposed. Here we show how the drivers impact results would change for different assignments. Table B-15 shows the alternative assignments.

Legal and financial costs were originally assigned to learning by-deployment, in the case 1 we assigned them to 20% learning by researching and 80% learning by-deployment, by considering any possible influence of variation of warranty provisions linked with the turbine quality, and thus with R&D improvements.

Delivery costs were originally assigned to learning by-deployment, learning by-researching and market dynamics with a certain share. Here, we considered in case 1 a mayor contribution of learning by-researching as an improvement in distribution equipment, and market dynamics related to greater ability of adaptation to rules in new sales markets.

Supplier and other costs component is a residual, in case 1 we included a 15% of learning by researching impact due to the presence of electricity grid connection costs as one of the sub-components in this category. Hence, R&D improvements obtained in the HV grid can contribute to reduce these costs; we removed 5% from the other categories as a consequence.

In case 2 we did not account for the supplier and other cost category, considering it as unknown category, only well-known components were analysed with drivers**.**

Table B-15 Assumptions sensitivity analysis

Techno-economic variables/ Cost components	**Drivers**	**Base case: contribution to cost component (%)**	**Case 1**	**Cas5e 2**
Materials amount	LEARNING BY-RESEARCHING	100%	100%	100%
Materials price	SUPPLY-CHAIN DYNAMICS	100%	100%	100%
Energy/electricity price	SUPPLY-CHAINDYNAMICS	100%	100%	100%
Energy/electricity consumption	LEARNING BY-DEPLOYMENT	100%	100%	100%
Salary	SUPPLY-CHAIN DYNAMICS	100%	100%	100%
Employees productivity	LEARNING BY-DEPLOYMENT	100%	100%	100%

Capital depreciation	LEARNING BY-DEPLOYMENT	100%	100%	100%
Delivery costs	LEARNING BY-DEPLOYMENT	50%	30%	50%
	LEARING BY-RESEARCHING	30%	40%	30%
	MARKET DYNAMICS	20%	30%	20%
Financial and legal costs	LEARNING BY-DEPLOYMENT	100%	80%	100%
	LEARNING BY-RESEARCHING	-	20%	-
R&D costs	LEARNING BY-RESEARCHING	100%	100%	100%
Suppliers & others costs	LEARNING BY-DEPLOYMENT	50%	45%	Not included
	SUPPLY MARKET DYNAMICS	25%	20%	
	MARKET DYNAMICS	25%	20%	
	LEARNING BY-RESEARCHING	-	15%	
Head company profit	MARKET DYNAMICS	100%	100%	100%

The results in case 1 show that during the first period learning by-researching remains the lower impact driver, this impact increased during the second period overcoming the contribution of supply chain dynamics and market dynamics. This is expected in this case, because in this case it is assumed that electricity grid costs are part of the residual category and they reduce their costs through R&D investments overcoming any grid availability bottle necks. This sensitivity is just speculation missing more information to analyse this costs category with more detail.

Table B.-16 Results sensitivity, case 1

Contribution to cost changes (%) CASE 1	2005-2008	2008-2017	2005-2017
Learning by-researching	15%	22%	27%
Learning by- deployment	36%	41%	46%
Supply Chain dynamics	27%	19%	13%
Market dynamics	22%	18%	14%

The drivers impact related to the only known cost categories (case 2) as shown in the following table. Learning by-deployment remains the main driver impacting for each time-period taken into consideration. Interestingly, the contribution of learning by-researching increased to 26% during the second period overcoming the contribution of supply-chain and market dynamics. The increased impact of learning by researching during the second period, and considering the whole period, is also observed in the base case even if with a lower slope, this contribution is given to increase R&D investment in the company to improve the technology and successful achievement in material costs efficiency.

Table B.-17 Results sensitivity, case 2

Contribution to cost changes (%) CASE 2	2005-2008	2008-2017	2005-2017
Learning by-researching	8%	26%	41%
Learning by- deployment	36%	43%	50%
Supply Chain dynamics	35%	17%	3%
Market dynamics	21%	14%	6%

Appendix C

C.1 Cobb-Douglas function to derive a learning curve

Here as follow the theoretical model to derive the log form of a MFLC is presented.

Following [51] the MFLC model is derived from a standard Cobb-Douglas cost function (Eq. 1).

$$C_{unit} = a \cdot Q_x^{\frac{1-r}{r}} \cdot \left(\prod_{i=1}^{m}\left(q_i^{\alpha_{LD_i}}\right)\right)^{1/r} \cdot \left(\prod_{i=1}^{n}\left(P_i^{\alpha_{IM\,i}}\right)\right)^{1/r} \qquad \text{(C.1)}$$

Where:

C_{unit} is unit cost,

Q_x is fixed level of output generated (i.e. plant size). Representing the scale effect of economies of scale, where the term r is the return-to-scale index,

q_i is learning variable according to the learning driver associated (i.e. learning by-doing, by-researching, by-interacting), and the α_{LD_i} are learning curve elasticities for each learning driver,

$\left(\prod_{i=1}^{n}\left(P_i^{\delta_i}\right)\right)^{1/r}$ the product of input prices P_i (i.e. material, labour), and α_{IM_i} are the input price elasticity,

a residual factor.

Eq. C.1 can be written in a double-log scale form, the basic empirical model obtained is the expression used to represent a MFLC, by assuming $\log(a) = b_0$; $\frac{\alpha_{LD_i}}{r} = b_{LD_i}$; $\frac{1-r}{r} = b_{SE}$, and $\frac{\alpha_{IM_i}}{r} = b_{IM_i}$, the equation can be written as in Eq. C.2:

$$\log C_{unit} = b_0 + -\sum_{i=1}^{m} b_{LD_i} \cdot \log(q_i) + b_{SE} \cdot \log Q_x + \sum_{i=1}^{n} \cdot b_{IM_i} \cdot \log(P_i) + \varepsilon \qquad \text{(C.2)}$$

Where:

$b_0, b_{LD_i}, b_{SE}, b_{IM_i}$ are the learning index estimated during the linear regression analysis from which the learning elasticity can be derived, and ε is the additive error term.

According to each combination of learning drivers, different learning curves can be built and from the learning elasticity identified for each learning driver the learning rates can be estimated with the equation:

$$\mathrm{LR}_i = 1 - 2^{\alpha_i} \tag{C.3}$$

Learning rates show the percentage change in the unit costs associated with a doubling of the learning factor associated to that learning driver.

Multiple Cobb-Douglas functions that can be developed, depend from the combination of the learning drivers included, scale effect and input material (as showed in the review done in Chapter 2 of this thesis). The choice of the type of learning curve and the learning factor to adopt is according to the case study analysed.

The simplest empirical model is the 1FLC which consider only combination of one driver, specifically learning by-doing or learning by-deployment. The expression of 1FLC becomes:

$$\log C_{unit} = b_0 + b_{LBD} \cdot \log(q_{LBD}) + \varepsilon \tag{C.4}$$

Where:

b_0, b_{LBD} are the learning indexes estimated during the linear regression analysis, and q_{LBD} the learning variable associated to learning by-doing.

Explanation about the simplicity of this expression and the trade-offs with more complex learning curves is explained in section 1.2.4.

C.2 Forgetting by-not doing concept

When the learning by-researching driver is included in the equation, the learning variable associated with learning by-researching most commonly used is the R&D knowledge stock, it is evaluated as:

$$\mathrm{KS_y} = (1 - \delta)\mathrm{KS_{y-1}} + \mathrm{R\&D_{y-tlag}} \tag{C.4}$$

It is defined as a function of the cumulative RD&D yearly investments (from base year to time y), taking into account the depreciation rate δ, expression of the obsolete research that is not providing new insight anymore, and the time-lag, $tlag$, the time interval between the investment moment and the visible effects in the productivity. To use R&D knowledge stock instead of the other learning variables allows to evaluate the phenomenon of "**forgetting by not-doing**". If the research is not done anymore the depreciation rate will reduce the value of learning by researching and thus the price may increase even if there are not change in the production [27].